Yale University
EliScholar – A Digital Platform for Scholarly Publishing at Yale

Yale Graduate School of Arts and Sciences Dissertations

Spring 4-1-2021

Essays on Labor Economics

Marianne Bernatzky Koehli
Yale University Graduate School of Arts and Sciences, marianne.bernatzkykohli@yale.edu

Follow this and additional works at: https://elischolar.library.yale.edu/gsas_dissertations

Recommended Citation

Bernatzky Koehli, Marianne, "Essays on Labor Economics" (2021). *Yale Graduate School of Arts and Sciences Dissertations*. 12.
https://elischolar.library.yale.edu/gsas_dissertations/12

This Dissertation is brought to you for free and open access by EliScholar – A Digital Platform for Scholarly Publishing at Yale. It has been accepted for inclusion in Yale Graduate School of Arts and Sciences Dissertations by an authorized administrator of EliScholar – A Digital Platform for Scholarly Publishing at Yale. For more information, please contact elischolar@yale.edu.

Abstract

Essays on Labor Economics

Marianne Bernatzky Koehli

2021

The first chapter studies the life-cycle behavior of two cohorts of American women: those born in the 1960s and those born in the 1980s. Millennial women are more likely to work full time, work in professional, health, and education-related occupations, and be childless in their mid-thirties than women born in the 1960s. I build a life-cycle model that incorporates labor supply, occupation, and fertility choices, and estimate the model for the older cohort. I analyze the role of two forces in explaining the data patterns: (i) labor market factors, including changes in the wage structure and in the initial joint distribution of workers' skills and occupations' skills requirements, and (ii) family factors, including changes in marital status across cohorts. I find that both mechanisms are important and together are able to (i) explain the changes in occupational sorting across cohorts; (ii) predict 74% of the changes in the share of women in full-time work; (iii) explain 85% of the decrease in the share of women with two children and (iv) explain 81% of the increase in the share of childless women in their mid-thirties.

The second chapter, which is work performed jointly with Lucas Finamor and Boryana Ilieva, studies women and men's labor market and insurance decisions around childbirth in Chile, a country with widespread informality. We identify three sectors of employment: formal, informal and self-employment. An individual in the informal sector works in a private firm without a labor contract and a self-employed person is an independent worker. We document the following findings. First, there are no significant changes in the share of workers with no labor contract after childbirth

for both men and women, but women are more likely to switch into self-employment where the effect is larger for those highly educated. Second, we show that highly educated women are more likely to work remotely after the first birth. In contrast, low educated women do not change work location. Third, women are also more likely to switch to less cognitive intensive occupations after childbirth, which may explain the fall in wages after the event. Fourth, women are less likely to keep private health insurance after their first birth. Finally, we explore the effects of the 2008 Chilean pension system reform on formal work decisions. We observe that women who had children after 2008 are less likely to leave formal employment, in comparison to women who had children before the reform was implemented.

In the third chapter, which is joint work with Paula Calvo and Zhengren Zhu, we investigate the role of maternal mental health on children's cognitive and mental health development. We propose a model that incorporates maternal mental health as a separate input in the human capital production function, different from cognitive and non-cognitive skills. We employ the National Longitudinal Survey of Youth 1979, where we link mothers and their children, to document the empirical patterns that motivate this study: First, poor maternal mental health is positively associated with poor mental health of her child and negatively associated with her child's cognitive development (which includes math and reading recognition). Second, poor maternal mental health is associated with worse parental practices at different ages. Third, children's mental health problems affect their cognitive outcomes in school. Fourth, children with poor mental health are more likely to have mental health problems in adult life, have lower wages and lower educational attainment. Our model incorporates these key mechanisms. We describe the estimation steps and propose counterfactual exercises.

Essays on Labor Economics

A Dissertation
Presented to the Faculty of the Graduate School
of
Yale University
in Candidacy for the Degree of
Doctor of Philosophy

by
Marianne Bernatzky Koehli

Dissertation Directors: Costas Meghir, Joseph Altonji and Ilse Lindenlaub

June 2021

Copyright © 2021 by Marianne Bernatzky Koehli

All rights reserved.

To the memory of Abuela Lidia, a loving and devoted grandmother, who moved heaven and earth to give her granddaughters a future.

Contents

List of Figures

List of Tables

Acknowledgments

To my advisors Costas Meghir, Joseph Altonji and Ilse Lindenlaub, who invested an invaluable amount of time guiding me, educating me and motivating me. It was a great privilege being your student all these years.

To Cormac O'Dea, who supported and guided me through my research process.

To my mother, and my wonderful sisters Helen and Ingrid, who encouraged me to carry on with a smile when I faced challenges and felt disoriented, and believed in me every step of the way.

To Luis Monteiro, for his love, kindness, and constant support. You are always by my side and you make me a better person everyday. I am infinitely grateful for that.

To Florencia De Luca and Viviana Rocco, who motivated me and always had words of support. I am particularly thankful for our talks at the backyard fire pit under the stars.

To Suk Joon Son, for our long walks, philosophising and discussing our research. You are the most argumentative friend.

To my dear Brazilian friends and neighbors, Lucas Finamor, Ana Carolina Diniz, Fernando Cordeiro, Sabrina Lacerda and Eduardo Fraga. I am grateful for your laughter and our weekly meetings playing cards and board games.

To the Catholic community at Saint Thomas More Chapel, and to my friends Armando Perez-Gea and Javier Gonzalez. You were a solid anchor and my family every Sunday.

To my friends and colleages, Julian Aramburu, Paula Calvo, Boryana Ilieva, Daniela Morar, Mariana Sans, Oscar Soler, Jaehee Song and Zhengren Zhu, with whom I shared many productive conversations on research.

Chapter 1

Labor Market Behavior and Fertility of Highly Educated Women

1.1 Introduction

Highly educated women in the United States have drastically changed their labor supply, occupation, and fertility choices over the last 40 years. When comparing the share of women in full-time employment of two cohorts, those born in the 1960s and those born in the 1980s, I observe that women in the younger cohort are more likely to work full time, especially during their early thirties, the most common child rearing years. Occupational sorting also shows significant changes. Women in the younger cohort are more likely to work in professional, health, and education-related jobs, which demand high cognitive and social skills. This change comes as women leave traditionally female clerical jobs, including secretarial and administrative assistant positions. At the same time, fertility behavior has changed, as women in the younger cohort are more likely to be childless or have a smaller number of children in their mid 30s.[1]

The goal of this paper is to construct a life-cycle model of labor supply, occupational choice, and fertility decisions that can *jointly* explain these changes. I explore the extent to which variation in labor market incentives and in family formation can generate the patterns observed in the data. Studying the changes in behavior in a unified way allows for a better understanding of how a change in the wage structure that affects labor supply and occupational choices also influences fertility outcomes, and how a change in family formation that directly affects fertility outcomes has spillover effects on labor market outcomes. In addition, apart from studying the main drivers of changes in behavior of highly educated women, my analysis sheds light on the forces that contribute to the reduction in the occupational gender gap, especially in managerial and professional sectors (Blau and Winkler (2017)).[2]

I build a life-cycle model with three endogenous decisions: labor supply, occupation, and fertility. The first choice involves working part-time, full-time, or not at all. The second choice involves choosing among five different occupations: (i) manager/professional, (ii) health/education, (iii) services, (iv) clerical, and (v) science. The third is a fertility choice, where a woman decides to have a child or not, conditional on her fertility status. In each period, there is a probability of being single, married to a low educated husband or married to a highly educated husband. This process is exogenous, and transition probabilities are estimated from the data. There is also a probability of being fertile in each period; this evolves with age mirroring the biological clock.[3] In the model, women have cognitive and social skills. Occupations differ in their cognitive and social skill requirements, mea-

[1] See also Heck, Schoendorf, Ventura, and Kiely (1997), Blau and Winkler (2017), Cortes, Jaimovich, and Siu (2018).

[2] Highly educated women increased participation in managerial and professional jobs, while men experienced no changes across cohorts (Figure 1.7 in Section 1.8.1).

[3] These probabilities are taken from Trussell and Wilson (1985).

suring the degree to which these skills are needed to perform tasks in a particular occupation. I consider cognitive and social skills as the two major skill dimensions of highly skilled individuals, along which they sort in the labor market. Each skill type accumulates depending on the complementarity between a worker's skills and the current occupation skill requirements. Thus workers accumulate more skills in occupations in which they are more productive. Women also accumulate experience by working, with the accumulation rate depending on age and hours of work. This feature makes early career interruptions very costly and allows the model to explain the empirical timing of fertility. Wages are a function of a worker's skills, current occupation's skill requirements, mismatch between the skills of the worker and the skill requirements of her occupation (a source of wage penalty that grows based on the distance between these two factors), and experience. Wages are an important determinant of occupational and labor supply choices, which can also affect fertility outcomes.

My model has a number of distinct features. First and most importantly, I consider choices related to labor supply, occupation, and fertility *jointly*. The decision to have children is not independent of the choice of how many hours to work or which occupation to select, so variations in the returns to workers' skills and skill requirements of occupations will have implications for fertility decisions. In a similar way, family formation changes that affect fertility, such as changes in marriage patterns, will also affect labor supply decisions. Second, occupations in my model differ in their skill requirements. The requirements affect wages, not only directly but also through skill mismatch. Third, individuals have multiple observable skills that accumulate over the life cycle. These skills are relevant for occupational choice, as women find it desirable to sort into occupations favorable to skill accumulation. However, aiming too high is costly because the mismatch is penalized by lower wages.

It is important to highlight that the return to skills, skill requirements, and the skill mismatch differs by skill dimension.

To motivate my analysis, I use data from CPS, NLSY79, NLSY97 and O*NET to obtain measures of workers' skills, requirements of occupations, and to document the key empirical facts. I use the Armed Forces Qualifying Test (AFQT) as a proxy for cognitive skills, and measures of non-cognitive skills and youth delinquency behavior as proxies for social skills.[4] In order to construct the measure of cognitive and social skill requirements, I consider a set of O*NET descriptors that capture, respectively, core analytical tasks and tasks that involve social interactions.

Three key patterns emerge: (i) there is an increase in the share of women employed in full-time work across cohorts, especially during their thirties (from 52% to 60%); (ii) women are increasingly employed in managerial, professional, health, and education-related jobs, which have high requirements for cognitive and social skills, and decreasingly employed in clerical jobs; and (iii) there is an increase in the share of childless women among women in their mid-thirties (from 27% to 35%), as well as a decrease in the share of women with two children (from 34% to 27%).

I estimate the model using the method of simulated moments (McFadden (1989), Pakes and Pollard (1989)) for the cohort of women born in the 1960s and show that the model fits the data well. I then use these estimates to conduct counterfactuals. Given preferences fixed to the 1960 level, I explore the role of two channels that can shape decisions on labor supply, occupation, and fertility. The first channel concerns the changes across cohorts in the wage structure, in the initial joint distribution of workers' skills, and in occupations' skills requirements. I refer to this as the 'Labor Market' channel. The second channel concerns the changes in the prevalence of marriage across cohorts, which refer to different transition rates into and out

[4] I take the AFQT scores from Altonji, Bharadwaj, and Lange (2012).

of marriage. I refer to this as the ‘Family’ channel. I provide empirical evidence illustrating the changes over time. In reference to the ‘Labor Market’ channel, wage regressions across cohorts show an increase in the importance of cognitive and social skill requirements on wages, and an increase in the mismatch cost of social skills. In addition, there are changes in mean skill requirements for various occupations across cohorts, where, for example, clerical and science occupations have increased their cognitive and social requirements. The initial joint distribution of workers’ skills does not change much across cohorts. With respect to the ‘Family’ channel, I observe that women born in the 1980s (the later cohort) are more likely to be single than women born in the 1960s.

I run three counterfactual exercises. In the first counterfactual, I set the wage structure, initial distribution of workers’ skills, and skill requirements of occupations to those of the 1980 cohort, while keeping all other parameters at their 1960 level. I find that the ‘Labor Market’ channel explains almost perfectly the changes in occupational sorting, where women increase employment in managerial, professional, health and education-related jobs, and decrease employment in clerical jobs. Changes in both the wage structure and occupations’ skill requirements are key to explaining the data patterns. The change in the wage structure creates incentives to move towards occupations that are intensive in cognitive and social skill use, such as health and education-related jobs. But this change alone generates too much employment in health and education jobs and too little in science and clerical jobs. The change in the mean skill requirements of occupations across cohorts counterbalances this extreme effect.

As women move into occupations with higher wages, they prefer to be employed full time to reap the full returns from working in such occupations. The changes in the wage structure across cohorts also involve a small increase in the returns to experience, contributing to the increase in full-time work. Overall, I find that the 'Labor Market' channel explains 56% of the overall change in the share of women working full time across cohorts. This mechanism also has an effect on fertility choice, explaining 25% of the overall decrease in the share of women with two children and 25% of the increase in the share of women who are childless. This result is consistent with the fact that in the model it is more costly to work longer hours when one has children, highlighting the interdependence of labor market and fertility choices.

In the second counterfactual exercise, I set marriage probabilities over the life cycle, initial distribution of children, and initial marital status to those of the cohort born in the 1980s. I show that the 'Family' channel explains 51% of the total change in the share of childless women and 50% of the overall change in the share of women with two children. The decline in marriage across cohorts increases the proportion of single women, which translates into different economies of scale at the household level, making children more expensive. In addition, there is a link between labor supply and fertility choices, because childcare costs are higher for women working longer hours. This channel is able to explain 18% of the change in full-time work. Finally, the 'Family' channel does not substantially change the incentives to switch occupations.

Finally, I run a third counterfactual exercise that combines both 'Labor Market' and 'Family' channels. The two together are able to (i) explain almost perfectly the changes in occupational sorting across cohorts; (ii) predict 74% of the increase in the share of women in full-time work; (iii) explain 85% of the decrease in the share of women with two children; and (iv) explain 81% of the increase in the share of childless women in their mid-thirties. Both the 'Labor Market' and 'Family' channels are needed to account for the observed changes in occupational sorting, full-time work, and fertility. The relation between labor supply and fertility decisions plays a vital role.

The rest of the paper is organized as follows. In Section 1.2, I review the related literature. In Section 1.3, I describe the data and key empirical patterns that motivate this paper. In Section 1.4, I describe the model. In Section 1.5, I introduce the estimation procedure, discuss parameter estimates and model fit. In Section 1.6, I carry out my main counterfactual exercises to explore how labor market and family changes affected occupational sorting, labor supply and fertility choices across cohorts. In Section 1.7, I conclude.

1.2 Related Literature

The aim of this paper is to unravel the causes behind highly educated women's change in labor supply, occupation and children choices across cohorts. I develop a framework that includes these three endogenous choices and that allows performing counterfactuals to assess the relative importance of labor market and family changes as key drivers of these outcomes. This paper contributes to three strands of the literature: research on recent changes in women's labor market and fertility behavior; multi-dimensional heterogeneity and matching; and literature on structural approaches to study labor supply, occupation, and fertility choices in a dynamic setting.

Changes in Women's Labor Market and Fertility Behavior. There are several explanations in the literature for why the labor supply of women has increased over time. These typically focus on the extensive margin and on older cohorts. Works in this vein examine: change in divorce laws (Stevenson (2008), Fernández and Wong (2014), Voena (2015)), lower childcare costs (Attanasio, Low, and Sánchez-Marcos

(2008)), cultural change (Fernández (2013), Goussé, Jacquemet, and Robin (2017)), change in wages (Eckstein and Lifshitz (2011), Goussé, Jacquemet, and Robin (2017) Eckstein, Keane, and Lifshitz (2019)), home production technology (Greenwood, Seshadri, and Yorukoglu (2005)), and decreasing discrimination (Jones, Manuelli, and McGrattan (2015)). There is little evidence with respect to changes in the intensive margin over time, but exceptions are Olivetti (2006) and Ngai and Petrongolo (2017). On the fertility dimension, existing literature focuses on the role of wages and marriage market (Caucutt, Guner, and Knowles (2002)) and contraception technology (Eckstein, Keane, and Lifshitz (2019)) to explain fertility decisions. These papers address changes for older cohorts as well. There is a growing body of literature that focuses on women's increased participation in services and socially intensive jobs (Borghans, Ter Weel, and Weinberg (2014), Cerina, Moro, and Rendall (2017), Ngai and Petrongolo (2017), Cortes, Jaimovich, and Siu (2018)). With the exception of Ngai and Petrongolo (2017), which studies the rise in the services sector and female hours, these papers focus on occupational choices, without taking into account hours, fertility choices, or life-cycle considerations in occupational choices.

Multi-dimensional Heterogeneity and Matching. There is a vast and growing body of literature on multi-dimensional human capital, where workers are characterized by various skills (e.g.: cognitive, manual, social) and work in occupations that differ in the tasks intensity (Gathmann and Schönberg (2010), Deming (2017), Lindenlaub (2017), Taber and Roys (2019), Atalay, Phongthiengtham, Sotelo, and Tannenbaum (2020), Guvenen, Kuruscu, Tanaka, and Wiczer (2020), Lise and Postel-Vinay (2020), Tan (2020)). My paper is closest to Lise and Postel-Vinay (2020) and Taber and Roys (2019), who use a life-cycle approach, with workers' skills evolving over the life-cycle and accumulation depending on the occupations' skill requirements. I also build on Guvenen, Kuruscu, Tanaka, and Wiczer (2020) as wages depend on the skill mismatch, measured as a distance between a worker's skills and the occupation's skill requirements. All these papers, however, are focused on the behavior of men and do not incorporate important life-cycle considerations such as hours of work, family formation, or fertility.

Dynamic Models with Labor Supply, Occupation, and Fertility Choices. I build on other papers that develop dynamic models to study women's life-cycle behavior, such as Eckstein and Lifshitz (2011), Fernández and Wong (2014), Blundell, Costa Dias, Meghir, and Shaw (2016), Adda, Dustmann, and Stevens (2017), and Eckstein, Keane, and Lifshitz (2019). The closest to mine is Adda, Dustmann, and Stevens (2017), which is the only other paper to the best of my knowledge that incorporates the three endogenous choices on which I focus. Both my model and my objectives differ from those of Adda, Dustmann, and Stevens (2017) in the following respects. First, their purpose is to quantify the career costs of children, while my objective is to understand what drives changes in women's occupational sorting, labor supply and fertility across cohorts. Second, individuals have multiple observable skills that accumulate over the life cycle. These skills are relevant for occupational choice, as women find attractive to go to occupations where they accumulate more of their skills, but at the same time they are aware of potential wage penalties arising from skills mismatch. In Adda, Dustmann, and Stevens (2017), individuals differ in unobserved ability and experience. Further, I also focus on highly educated women (college or more), while Adda, Dustmann, and Stevens (2017) focus on women who attend low track schools. Third, occupations in my model differ on skill requirements, which affect wages not only through a direct impact but also through skill mismatch. While Adda, Dustmann, and Stevens (2017) incorporate the fact that different occupations have different wage paths, I opt for a more parsimonious wage function where wage differences across occupations arise from observable characteristics (i.e., task intensity). The introduction of heterogeneity in skills and skill requirements of occupations is vital to analyzing the changes in occupational sorting over time, as women have incentives to switch to occupations that are cognitive and socially intensive, such as managerial, professional, education and health-related jobs.

1.3 Data and Descriptive Evidence

1.3.1 Data

In my analysis, I concentrate on women in the United States who have at least a college degree.[5] I draw on five datasets: Current Population Survey (CPS), National Longitudinal Survey of Youth 1979 (NLSY79), NLSY97, Occupational Information Network (O*NET) and Survey of Income and Program Participation (SIPP).

The CPS dataset provides information on employment, hours of work and occupational choices for cohorts born in the years 1956-1960 and 1980-1984.[6] I call these cohorts throughout this paper the '1960 cohort' and the '1980 cohort', respectively. I define a full-time worker as one who works more than 35 weekly hours. In order to have a consistent classification of occupations over time, I use crosswalk files from Autor and Dorn (2013) and I further organize workers into five groups: (i) manager/professionals, (ii) health/education, (iii) services, (iv) clerical, and (v) science. In the case of the science occupations, I also include engineers and computer scientists.

The NLSY79 and NLSY97 datasets track national representative samples of in-

[5]I focus on women with a college degree because they are the ones that increase full-time work, move into professional occupations and delay fertility the most in their early thirties.

[6]Data from IPUMS-CPS, University of Minnesota, www.ipums.org (Flood, King, Rodgers, Ruggles, and Warren (2020)).

dividuals who were 14-22 and 12-17 years of age, respectively, when first interviewed in 1979 and 1997. I build a panel from 1979 to 2016 for NLSY79 and another from 1997 to 2017 for NLSY97. These provide information on labor supply, wages, worker skills, children, marital status and occupation for each individual. In both cases, I retain highly educated women and exclude poor white women and women in the military in the NLSY79 sample, and 'mixed race women' in the NLSY97 sample.[7] The subsamples used in this study have 1,433 individuals for NLSY79 and 1,756 individuals for NLSY97. For the construction of tables and empirical analysis, I retain women between 24 and 46 years old for both datasets, as fertility is completed by one's mid-forties.[8]

The O*NET dataset offers detailed measures of skills, abilities and knowledge required to perform tasks in different occupations.[9] I use this dataset to construct the two-dimensional vector of job tasks: cognitive and social. I work with the version 9.0, which includes information on over 970 occupations. For each of them, O*NET gives a score for the relevance of 277 descriptors. I use nine of these descriptors that are most related to the skills I select from NLSY79 and NLSY97.

I also use the SIPP to obtain weekly childcare costs for women working full time and part time. I use the data from wave 1993, a time when mothers in NLSY79 were in their mid-thirties.[10]

Worker Skills

I construct the cognitive and social measures of a worker's skills using the Armed Forces Qualifying Test (AFQT) score and measures of social skills. More specifically,

[7] White poor women were not followed after 1984 for NLSY79 and women could not identify as mixed race in NLSY79.

[8] For NLSY97, I have information on respondents until age 37.

[9] This data set is developed under the sponsorship of the U.S. Department of Labor/Employment and Training Administration.

[10] Data from https://www.census.gov/data/tables/1993/demo/ppl-138.html.

to serve as proxies for cognitive skills, I rely on AFQT scores from Altonji, Bharadwaj, and Lange (2012). To obtain measures of social skills, I use the Rosenberg Self-Esteem Scale, the Ten-Item Personality Inventory and three measures of criminal behavior. In the last case, I run Principal Component Analysis (PCA) on this set of descriptors and keep the first principal component, which defines the social skills of the worker. Finally, I covert the measures of cognitive and social skills into percentile ranks and restrict the measure to the interval [0,1]. Similar measures of cognitive and social skills have been used in Deming (2017), Lise and Postel-Vinay (2020) and Tan (2020). I convert to percentile ranks as in Guvenen, Kuruscu, Tanaka, and Wiczer (2020) because the scales of skills and skill requirements are different, and as I consider the effect of mismatch between a worker's skills and the occupation's skill requirements on wages, I want them to be comparable.

Table 1.1 reports the correlation between workers' skills in our sample for (a) the 1960 Cohort and (b) the 1980 Cohort and shows that there is almost no correlation between social and cognitive skills.

Table 1.1: Correlation of Worker Skills

	(a) Worker Skills Cohort 1960		**(b) Worker Skills Cohort 1980**	
	Cognitive	**Social**	**Cognitive**	**Social**
Cognitive	1.00		1.00	
Social	0.18	1.00	-0.01	1.00

Note: Data from NLSY79 and NLSY97. I compute correlations on initial cognitive and social initial skills for the samples of 1,433 and 1,756 women for 1960 and 1980 cohorts, respectively.

Occupation Skill Requirements

The O*NET dataset provides job descriptors to build the cognitive and social skill requirements. In order to construct the measure of cognitive skill, I consider the measures ‘mathematical reasoning’, ‘number facility’, ‘memorization’, and ‘reading comprehension’, which capture core analytical tasks in the job. In a similar way, I select the measures ‘social perceptiveness’, ‘contact with others’, ‘assisting others’, ‘service orientation’ and ‘personal service’, which relate to social skills. Next, I aggregate O*NET scores at the SOC level, use a crosswalk to convert to Census Occupation codes, and finally convert to a time consistent classification of occupations using the crosswalk files from Autor and Dorn (2013).

I merge this occupation information with worker data from NLSY79 and NLSY97, I run PCA on these two set of descriptors, and keep the first principal components, which are the cognitive and social measures of an occupation. As a last step, I convert the principal components into percentile ranks, restrict the measures to the interval [0,1] and generate measures for five occupation groups. I report the skill requirements for the different occupation groups in Table 1.2. Manager, professional, and science occupations have the highest cognitive skill requirements for both NLSY79 and NLSY97 samples. These occupations differ in terms of the social skills component, as science requires very few such skills. Health and education-related occupations require the highest levels of social skills, but the level of cognitive tasks is below that of professional occupations. Occupation requirements change across cohorts. For example, science occupations increase the social skill requirements (from 0.28 to 0.35) and clerical occupations increase the cognitive skill requirements (from 0.48 to 0.57). As the measures of occupation skill requirements are obtained through percentile ranks, there are two explanations for this. First, the increase in cognitive requirements of clerical occupations and in social requirements of science occupations, for instance, means that in the 1980 cohort there are more workers in clerical jobs with higher cognitive skill requirements and in science jobs with higher social skill requirements than in the previous cohort. This is a within-occupation group change in the skill requirements.[11] Second, the change in the distribution of occupations across cohorts can affect the mean percentile rank assigned to an occupation group. For example, the fall in the mean cognitive requirement for managerial and professional occupations can be affected by the fact that more women are employed in this occupation in the 1980 cohort.

Table 1.2: Skill Requirements of Occupations

	Cohort 1960		**Cohort 1980**	
Occupation	**Cognitive**	**Social**	**Cognitive**	**Social**
Manager/Professionals	0.82	0.49	0.80	0.51
Health/Education	0.42	0.72	0.41	0.69
Services	0.39	0.43	0.42	0.45
Clerical	0.48	0.35	0.57	0.36
Science	0.79	0.28	0.81	0.35

Note: Data from NLSY79 and NLSY97, women between ages 24 and 36 (to have consistent measures across cohorts). Columns report average cognitive and social skill requirements for each occupation group for 1960 and 1980 cohorts.

1.3.2 Descriptive Evidence

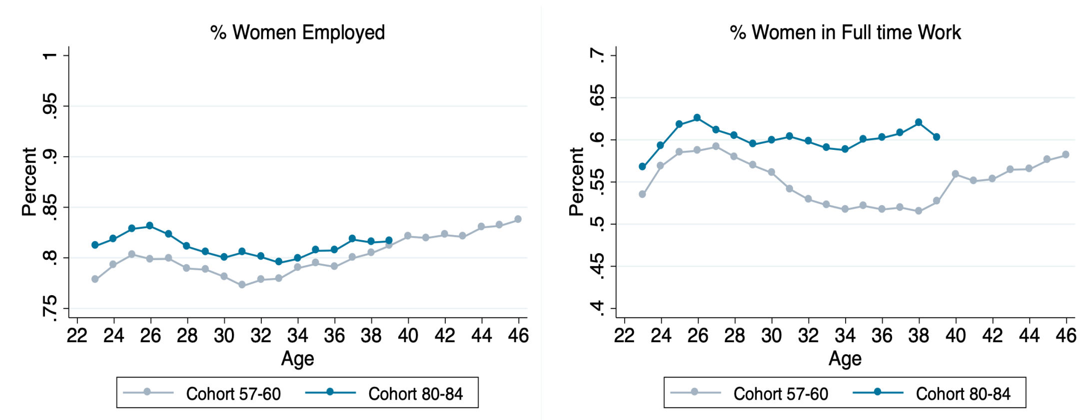
Key Patterns in the Data

In this section I document labor supply, occupation, and fertility patterns for highly educated women born in the 1960s and 1980s, respectively. Figure 1.1 reports the share of women employed and working full-time over the life-cycle. Highly educated women are very attached to the labor market, with employment rates around 80% for both cohorts. The most striking change is that the share of women in full-time work increased from 53% to 60% between the ages of 32 and 38. The number of hours worked by women in the younger cohort did not decrease over the life-cycle, unlike

[11] I observe that the raw mean scores of cognitive skill requirements for clerical occupations increase across cohorts as well as the raw mean score of social skill requirements for science occupations. This computation is performed using the raw score from principal component analysis normalized in an interval of [0,1].

the number of hours worked by women in the older cohort, which could potentially be related to changes in fertility choices across these cohorts, such as changes in motherhood or family size. In contrast to the behavior of highly educated women, highly educated men do not change their labor supply behavior (Figure 1.6 in Section 1.8.1).

Figure 1.1: Labor Supply of Highly Educated Women



Note: CPS data. Employment and Full-time work of highly educated women, for 1956-1960 and 1980-1984 cohorts. Full-time workers are defined as those individuals working more than 35 hours per week. The gray color represents the 1960 cohort and the blue color the 1980 cohort.

Taking a closer look at fertility patterns across cohorts, in Table 1.3 I show that the share of women with no children has increased over time, from 29% to 36% by the age of 37. By that age, the percentage of women with two children has also declined, from 34% to 27%. The share of women with one child is stable over time.

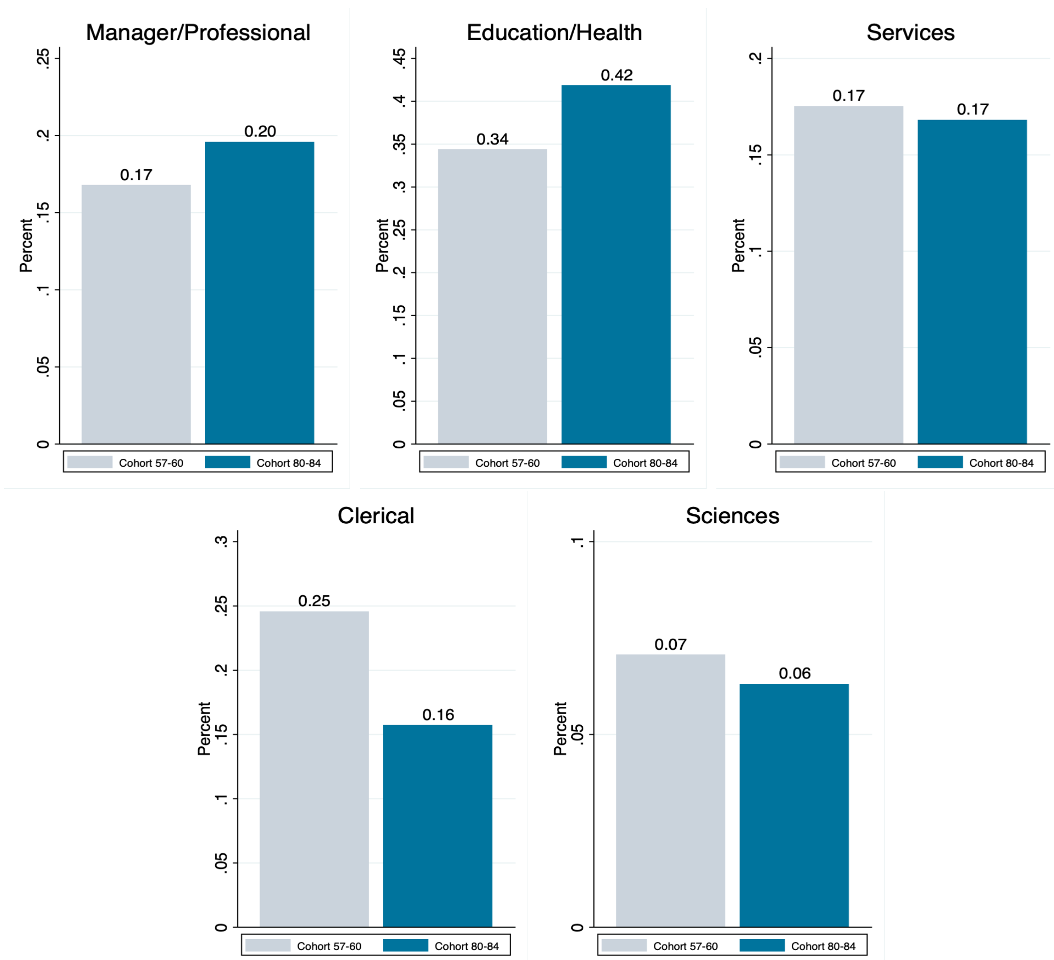
Table 1.3: Share of Highly Educated Women with different numbers of children

Age	**No Children**		**1 Child**		**2 Children**		**>3 Children**	
	Cohort							
	1960	**1980**	**1960**	**1980**	**1960**	**1980**	**1960**	**1980**
25	71%	72%	19%	17%	11%	10%	4%	3%
30	45%	50%	22%	22%	23%	18%	11%	10%
37	29%	36%	18%	18%	34%	27%	20%	18%

Note: Data from NLSY79 and NLSY97. Columns report the percentages of women with no children, 1 child, 2 children and 3 children or more by ages 25, 30 and 37 for 1960 and 1980 cohorts.

Figure 1.2 reports changes in occupational choices over time for the two cohorts based on CPS data. The share of women in professional, managerial, education, and health-related occupations increased over time, while the share of women in clerical jobs such as secretarial and administrative positions decreased over time. Importantly, the former occupational groups have higher cognitive and social skill requirements than those associated with clerical occupations (Table 1.2).

Figure 1.2: Occupational Choices of Highly Educated Women



Note: CPS data. Share of employed women in each occupation group, ages 22-32. The gray color represents the 1960 cohort and the blue color the 1980 cohort.

Potential explanatory mechanisms

One of the potential explanatory factors for the change in behavior in the labor market and fertility is the change in the wage structure over time, taken in conjunction with the change in the initial distribution of workers' skills and occupations' skill requirements. For instance, an increase in the returns of cognitive and social skill requirements would lead to different occupational sorting over time, as there are incentives to switch to occupations that highly demand these skills. Table 1.4 shows results from a regression where the dependent variable is ln wages and the regressors are skills of a worker, skill requirements of the current occupation (both cognitive and social), mismatch between the worker's skills and the occupation's skill requirements (measured by the absolute value of the distance between worker skills and skill requirements in the current occupation), and experience. In column (2) I observe that cognitive and social skills and skill requirements have positive returns. A mismatch in the cognitive dimension has a negative impact on wages, whereas the coefficient for the social mismatch is not significant.[12]

Column (4) shows that the return to cognitive and social requirements increased across cohorts, but more so in the social dimension. This change may have an impact on occupational sorting, where workers find incentives to move toward high-cognitive and high-social occupations. In addition, the change in wages may potentially affect labor supply and fertility. These changes in wages are not independent of the change in the initial distribution of workers' skills and the occupational skill requirements, which also change across cohorts. The results from the model allow disentangling the individual contributions of each of these factors. I also observe that the mismatch

[12]In Section 1.8.2, I show alternative wage specifications, where I include positive and negative mismatches for under- and overqualification. I observe that the penalty on wages is driven by over qualification in the cognitive dimension. However, I chose to employ a parsimonious wage specification with absolute value on the skill mismatch.

in the social dimension becomes stronger across cohorts, which could disincentivize women to sort into high social occupations if they have a low level of social skills.

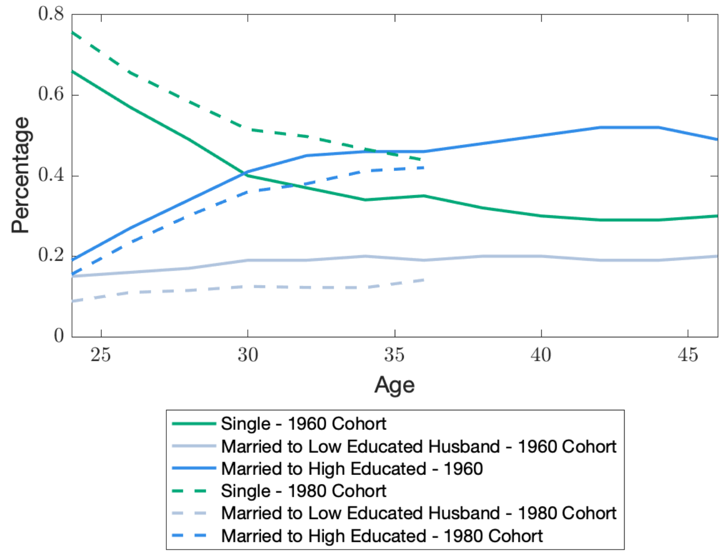
Table 1.4: Wage Regressions

	Regression of $\ln$ **wages**			
Cohort	**1960**	**1960**	**1980**	**1980**
	(1)	(2)	. (3)	(4)
Cognitive Skills (x_c)	0.350 ***	0.342***	0.372***	0.256***
	(0.0305)	(0.0298)	(0.0325)	(0.0327)
Social Skills (x_s)	0.153***	0.163***	0.121***	0.091**
	(0.0294)	(0.0290)	(0.0312)	(0.0308)
Cognitive Requirement (y_c)	0.892***	0.727***	1.292***	1.269***
	(0.0583)	(0.0579)	(0.0673)	(0.0674)
Social Requirement (y_s)	0.490***	0.428***	1.322***	1.245***
	(0.0523)	(0.0526)	(0.0685)	(0.0676)
$\|x_c - y_c\|$		-0.165**		-0.125***
		(0.0526)		(0.0559)
$\|x_s - y_s\|$		0.009		-0.078*
		(0.0429)		(0.0519)
Experience		0.037***		0.041***
		(0.00450)		(0.00461)
Constant	1.776***	1.660***	1.250***	1.031***
	(0.0435)	(0.0481)	(0.0622)	(0.0692)
R^2	0.109	0.163	0.148	0.210
Observations	10,933	10,933	15,302	15,302

Note: Data from NLSY79 and NLSY97, highly educated women ages 24-36. Columns show coefficients from a regression of ln wages that includes cognitive and social skills and skill requirements, mismatch on the cognitive and social dimensions defined as the absolute distance between skills and requirements, experience and a constant. Results are reported for the 1960 and 1980 cohorts. Wages are in 2016 constant dollars, and I trim values of the real hourly wage that are below 3 and above 200. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A second factor I explore is the change in marital status of women across cohorts. Figure 1.3 shows that the percentage of highly educated women who are single in their mid-twenties and early thirties is considerably higher in the younger cohort. This may potentially have implications for labor supply and fertility; I will explore such possibilities in the model.

Figure 1.3: Marital Status over the Life Cycle by Cohort



Note: NLSY79 and NLSY97 data. The categories are defined as follows: single, married to a low educated husband (high school or less) and married to a highly educated husband (more than high school). Solid lines represent women from the 1960 cohort and dashed lines from the 1980 cohort. In this definition of marriage, I do not consider cohabitation.

1.4 Model

In this section I describe the model I use to evaluate the mechanisms underlying the changes in labor supply, occupation, and fertility of highly educated women. Each woman maximizes the present value of her utility over a finite horizon and makes three choices. The first choice involves whether to work part time, full time or not at all. The second choice involves choosing among five different occupations: (i) manager/professional, (ii) education/health, (iii) services, (iv) clerical and (v) science. The third choice is about fertility, where the woman decides to have a child or not, conditional on her fertility status. She can have up to three children. Each period is two years and the period under consideration begins at the age of 24 and ends at the age of 45. I only consider highly educated women, and so I take education as given.[13]

In each period, a woman may be fertile or infertile, and there is uncertainty with respect to fertility status (f_t) in the next period. The probability of being fertile evolves over the life-cycle, reflecting the nature of the biological clock. Women may be married or unmarried, with transitions occurring randomly over the life cycle according to a stochastic process that depends on age, following the pattern I observe in the data. Although I treat marriage as an exogenous process, I account for marital sorting by specifying three categories: single, married to a low educated husband, and married to a highly educated husband. The marriage probabilities reflect observed sorting patterns.

Observed heterogeneity in the model is captured by the set of cognitive (x_c) and social skills (x_s), which evolve over the life cycle depending on the occupation in which an individual is employed and her employment status.[14] I do not include unobserved skill heterogeneity in my model because I have rich information on observable characteristics that determine a worker's productivity such as test scores and personality traits. Women also differ in unobserved preference for work, which is random and drawn at the beginning of their working lives. Occupations are defined by a set of cognitive and social skill requirements (y_c, y_s as described in Table 1.2). Occupation taste shocks affect individual's choices and, along with skill accumulation, generate occupational mobility. This is captured by the term ν.

The rest of this section discusses the utility function and decisions; human cap-

[13]Changes in the labor market and marriage market incentives may have an impact on college education decisions, changing the characteristics of women with at least a college degree (Bronson (2015), Guvenen and Rendall (2015), Chiappori, Dias, and Meghir (2018)). In order to analyze potential differences in observable characteristics of highly educated women across cohorts, I take the raw scores of cognitive and social skills for the 1960 and 1980 cohorts together and compute percentile ranks. I find that the means of cognitive skills are 0.48 and 0.51 for the 1960 and 1980 cohorts, respectively. The overall distributions are quite similar across cohorts. In the case of social skills, the means are 0.49 for both cohorts.

[14]I discretize the state space for cognitive and social skills of the worker into five and four types, respectively. This makes a total of 20 types of workers combining their social and cognitive skills.

ital accumulation and wages; marriage and fertility processes; and the individual maximization problem.

1.4.1 Utility Function, Constraints and Choices

In each period, a woman makes three choices. First, she decides on fertility $k_t \in \{0, 1\}$, which is the decision to have a child or not. Second, she chooses occupation $o_t \in \{1, 2, 3, 4, 5, Out\}$, which for modeling purposes includes non-employment Out. Third, she decides whether to work part time or full time $l_t \in \{PT, FT\}$, conditional on working. The deterministic part of flow utility is a linear function of consumption c_t, labor supply l_t, number of children n_t and occupation o_t. Consumption is adjusted by an equivalence scale eq that is a function of the household composition.[15] A woman may experience disutility from time spent at work which varies by whether she works part-time or full-time, and is captured by parameters $\gamma_1^{PT,m,\omega}$ and $\gamma_1^{FT,m,\omega}$. The subscript $\omega = \{1, 2\}$ represents permanent unobserved heterogeneity in the taste for work, which affects preferences for labor supply. There is heterogeneity by marital status, captured by the subscript $m \in \{married, single\}$. I also allow for the interaction of children and labor supply captured by $\gamma_2^{PT,m,j}$ and $\gamma_2^{FT,m,j}$. In the model, my subjects can have up to three children $j \in \{1, 2, 3\}$. In addition, women derive utility from the number of children represented by $\gamma_3^{m,j}$. Finally, women have a taste for the current occupation in which they are employed, denoted by γ_l^o, where $l \in \{1, 2, 3, 4, 5\}$. The permanent taste for given occupations refers to (i) manager/professionals, (ii) health/education, (iii) services, (iv) clerical and (iv) science. The parameters that capture work disutility, the interaction of children and

[15] I follow Blundell, Costa Dias, Meghir, and Shaw (2016) and consider $eq = 1$ for singles, 1.6 for couples, 1.4 for a mother with child, and 2 for a couple with children. An extension of this model would include an equivalence scale that is affected by the number of children instead of being affected only by their presence or absence.

labor supply, and the utility from children depend on marital status m (single or married).

$$u_t(c_t, l_t, n_t, o_t) = \left(\frac{c_t}{eq}\right) + \overbrace{\gamma_1^{PT,m,\omega}\mathbb{1}(l_t = PT) + \gamma_1^{FT,m,\omega}\mathbb{1}(l_t = FT)}^{\text{Work Disutility}} + \\ + \underbrace{\sum_{j=1}^{3}\gamma_2^{PT,m,j}\mathbb{1}(n_t = j)}_{\text{Working PT with children}} + \underbrace{\sum_{j=1}^{3}\gamma_2^{FT,m,j}\mathbb{1}(n_t = j)}_{\text{Working FT with children}} \\ + \underbrace{\sum_{j=1}^{3}\gamma_3^{m,j}\mathbb{1}(n_t = j)}_{\text{Utility from children}} + \underbrace{\sum_{l=1}^{5}\gamma_l^{o}\mathbb{1}(o_t = l)}_{\text{Utility from occupation}} \tag{1.1}$$

An individual's per-period budget constraint is defined as follows:

$$c_{it} = w_{it}h_t + 40w_{it}^h\mathbb{1}\left(m_{it} = married\right) - \kappa^{l_t}\mathbb{1}(\text{infant}_t = 1) \tag{1.2}$$

Consumption c_t is equal to the woman's earnings plus the husband's earnings if she is married ($m_t = married$), minus childcare costs if she has an infant child ($\text{infant}_t = 1$). The woman's earnings are defined as the hourly wage w_{it} multiplied by the hours h_t, which are 40 if she is working full time or 18 if she is working part time. The husband's earnings are defined as $w_{it}^h * 40$, where w_{it}^h is the hourly wage and 40 is the hours of work, as I assume that husbands are working full time. The fact that men are full-time workers is a common assumption in much of the literature (Attanasio, Low, and Sánchez-Marcos (2008), Fernández (2013), Adda, Dustmann, and Stevens (2017)).[16]

There are childcare costs to pay if a woman has an infant child (defined here as age less than 4 years old) and is working. I estimate the childcare costs for women working part time ($l_t = 1$) or full time ($l_t = 2$), which are captured in κ^{l_t}. In my

[16]My current model does not allow for income effects, a next step will extend this model to incorporate the interaction between the woman's consumption and her labor supply in the utility function.

current setup, the linear utility in consumption implies that agents do not seek to smooth consumption over time or over states of the world. Hence the inclusion of savings would not affect the labor supply decision. Also note that this static budget constraint is common in the modeling of dynamic labor supply (Eckstein and Lifshitz (2011), Eckstein, Keane, and Lifshitz (2019)).

1.4.2 Wages and Human Capital

Women have cognitive x^c and social x^s skills that depreciate by a constant rate δ_r, where $r \in \{c, s\}$. Skills also accumulate while women work, and the complementarity between a worker's skills x^r and the skill requirements y^r_o of her occupation plays an important role in learning (Gregory (2021)). The accumulation parameter γ_r is constant and skill specific. The law of motion for x^r is:

$$x^r_{it+1} = x^r_{it}(1 - \delta_r) + \gamma_r x^r_{it} y^r_{o_{it}} \tag{1.3}$$

Experience e_t accumulates depending on whether an individual is working part time or full time (l_t) and on the woman's age through the function $g(age, l_{it})$. This function takes value zero if the person is out of work, but its values need to be estimated for $l_t \in \{PT, FT\}$, i.e., part-time and full-time work. I allow for a different accumulation of experience depending on the age of the woman to capture the timing of fertility and the fact that career interruptions early in a career can be detrimental.[17]

$$e_{it+1} = e_{it} + g(age, l_{it}) \tag{1.4}$$

The wage is a function of a worker's skills x^r, the skill requirements of her current occupation y^r_o, the degree of mismatch between her skills and the requirements of

[17] In particular, I consider three stages: 24-31; 32-39 and 40-45.

the occupation $|x^r - y^r_o|$, and experience e.[18]

$$\begin{aligned} \ln w_{it} = \quad & \alpha_1 \quad + \sum_{r=c,s} \alpha_2^r x_{it}^r \quad + \sum_{r=c,s} \alpha_3^r y_{oit}^r \\ & + \sum_{r=c,s} \alpha_4^r |x_{it}^r - y_{oit}^r| \quad + \quad \alpha_5 ln(e_{it} + 1) \end{aligned} \tag{1.5}$$

There is measurement error ϵ_{it} in the wage, so observed wages are $\ln w^*_{it} = \ln w_{it} + \epsilon_{it}$.

1.4.3 Fertility and Marital Status

Women face an infertility shock $f_t = \{I, F\}$ in each period; it arrives at the beginning of the period with probability p. Once the shock is realized, and if the woman is fertile, she decides whether to have a child. If the woman is infertile, there is no choice to be made. I model infertility as an absorbing state; once infertile, a woman is infertile until the end of her life. Regarding marriage, there is a probability of being single, married to a low educated husband and married to a high educated husband in each period. Women consider both probabilities from marriage and fertility when making decisions.

1.4.4 Individual Maximization Problem

At the start of each period, individuals take as given the current state: $\Omega_t = \{t, x^c_t, x^s_t, e_t, n_{t-1}, \text{age}^K_{t-1}, f_t, m_t, \nu_t\}$. The state space is composed of variables set at the end of the previous period: number of children n_{t-1} and age^K_{t-1} of the youngest kid. It also comprises variables updated at the start of the period: age t, cognitive skills x^c_t, social skills x^s_t, experience e_t, fertility status f_t, marital status m_t and i.i.d extreme value distributed occupation shocks ν_t, with CDF $G_\nu = \exp(\exp(\frac{-\nu}{\sigma_\nu}))$.

[18] I am currently estimating the model with different wage specifications, including mismatches for over- and underqualification that are not symmetrical, as displayed in Section 1.8.2.

The value function for individual i in period t is:

$$V_t(\Omega_t) = \max_{o_t, l_t, k_t} \{u_t(c_t, l_t, n_t, o_t) + \nu_t(o_t) + \beta E_t V_{t+1}(\Omega_{t+1})\} \tag{1.6}$$

where β is a discount factor, and E_t is the expectation over future occupation preference shocks, fertility and marital status.

1.5 Estimation

The estimation of the model parameters follows a two-step procedure. First, I estimate some parameters outside of the model. Second, I estimate preference, female wages and human capital accumulation process parameters inside the model.

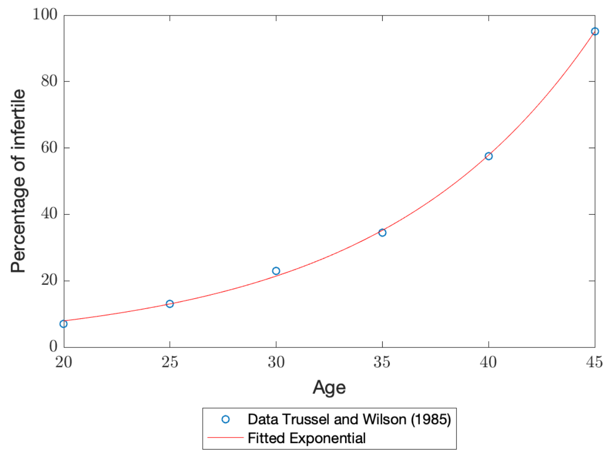
1.5.1 Parameters Estimated Outside the Model

Fertility Probability I set age-dependent probabilities of infertility following the literature on infertility risk (Sommer (2016), Trussell and Wilson (1985)). Even though these papers estimate the fraction of couples permanently infertile by the age of the wife, this is the closest estimation of infertility by age available in the literature.[19]

Marriage and Divorce Probabilities I estimate the probabilities of a partner arriving and leaving by age. Figure 1.5 shows the distribution of women into different marital statuses as a function of age: single, married to a low educated husband and married to a highly educated husband. The displayed simulated profiles are very close to the observed data ones. The data show that a woman who is highly educated is more likely to be married to a highly educated man, and the probability of this

[19]It would be better to use the fraction of women permanently infertile by age.

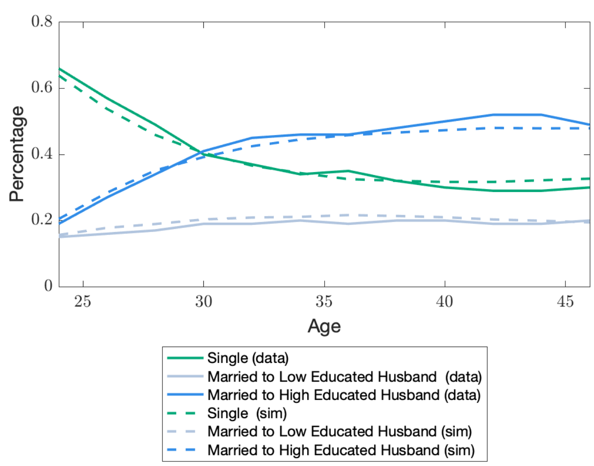
Figure 1.4: Fraction of Infertile Couples



Note: Data from Trussell and Wilson (1985) is displayed in blue dots, fitted by an exponential function (red line).

type of marriage increases with age. The share of women married to low educated husbands is low and increases only slightly over the life cycle. The estimated transition probabilities show that the probability of divorce is higher when an educated woman is married to a low educated man.

Figure 1.5: Marital Status of Highly Educated Women



Note: NLSY79 data. The categories are defined as follows: single, married to a low educated husband (high school or less) and married to a highly educated husband (more than high school). Solid lines represent shares of women in the different categories for the 1960 cohort that I observe in the data. Dashed lines represent simulation results for the 1960 cohort.

Other Pre-set Parameters I set the discount factor to 0.98 as in Voena (2015) and Reynoso (2019). I estimate the childcare costs from the Survey of Income and Program Participation (SIPP) dataset. I use data from Wave 9 (year 1993) to obtain childcare costs for women working part time and full time. In my model, I consider childcare expenditures for children under four years old, which is the definition I use of infant. Data from SIPP is reported for childcare expenditures for children under five years.

The wages of the husband are estimated from the data. The husband's log hourly wages are a function of education and age. The husband can have low education (high school or less) or high education (more than high school). The term ε_{it} represents measurement error.

$$\ln w_{it}^h = \alpha_{1,Ed}^h + \alpha_{2,Ed}^h age + \alpha_{3,Ed}^h age^2 + \varepsilon_{it} \tag{1.7}$$

Table 1.14 in Section 1.8.1 gives the estimates for the wage equation parameters for each type of husband.

1.5.2 Parameters Estimated Inside the Model

After inputting the estimates obtained outside the model, I proceed to estimate the remaining 49 parameters: 27 parameters for the utility function, ten human capital process parameters, eight wage parameters, three parameters related to unobserved heterogeneity in the taste for work, and the scale parameter of the extreme value-distributed occupational taste shocks.

Identification

The identification of the parameters in the model relies on the close relationship between each parameter and the behavior of women in the model. I construct 125 moments that aggregate individual behavior and have a counterpart in the data: shares of women out of work, in part-time work, and full-time work by age and marital status; shares across occupations; shares working part time and full time by number of children; shares with different children by age and marital status; wage moments; mean skill requirements while working and after periods of non-work; mean wage increase with cognitive and social complementarities; mean wage increase controlling for part-time work, full-time work, and experience in the previous period, and transitions.

I provide 'heuristic' identification arguments for the parameters in the model. As I observe a worker's initial skills, the skill requirements of an occupation, and experience, identification of the wage parameters is assured. Cognitive and social skills accumulation parameters are pinned down by analyzing how much wages grow with the interaction of worker's skills and the skill requirements of the occupation, as this interaction is fundamental for skill formation, itself an input in wages. Skill depreciation parameters are identified by the comparison of average cognitive and social occupation skill requirements of women at work with those who came back to work after a period of non-employment (in Equation 1.3 skills depreciate only for those who are not working, as there is no accumulation). I pin down experience accumulation parameters by studying how much wages vary with experience growth, and with part-time and full-time employment in the previous period for different stages in the life-cycle.

Choices are made conditional on exogenous and predetermined variables. Therefore, the proportions of women in each labor supply choice, in each occupation type, and with different numbers of children, will identify the parameters of the utility function. The distribution of types for taste for work, and the differences in utility parameters by type, are identified by the differences in choices made by women who are identical in terms of observable characteristics.[20] The scale parameter of the occupation taste shock is pinned down by transition rates across occupations.

Finally, to have a better understanding of which moments are most important to explain the estimates, I follow Andrews, Gentzkow, and Shapiro (2017) and Reynoso (2019) and study the sensitivity of parameter estimates to estimation moments.[21]

Method of Simulated Moments

I estimate the model using the method of simulated moments (McFadden (1989), Pakes and Pollard (1989)). For any vector of parameters, I simulate the model to produce a vector of 125 moments described above mom_{sim}.[22] These moments have a data counterpart mom_{data}. I use both a global and a local algorithm to search for parameter estimates. More formally, I need to find a vector of parameters θ such that I minimize the criterion function:

$$\theta_{SMM} = \arg\min(mom_{sim}(\theta) - mom_{data})' W^{-1}(mom_{sim}(\theta) - mom_{data}) \tag{1.8}$$

The matrix W is the weighting matrix, a diagonal matrix where the diagonal elements are bootstrapped sample variances of the $N = 125$ sample moments.

[20] An extension of this model would include unobserved taste for occupations. I could identify the share of people of each type by using data on occupation aspirations asked at the beginning of their working lives from NLSY79.

[21] $|\text{Sensitivity}| = |[D'_m W D_m] D'_m W|$. Results are available upon request.

[22] I perform 4300 simulations.

1.5.3 Results

Parameter Estimates

In this section I report the estimation results for the cohort born in the 1960s. Table 1.5, Table 1.6 and Table 1.7 give the estimates of the preference parameters, human capital accumulation parameters, wage parameters and their standard errors. The latter are calculated using the usual sandwich matrix.[23] Table 1.5 reports that the direct flow utility from part-time and full-time work is negative, where part-time work inflicts the smallest disutility. The utility cost of working is higher for single women, and this is consistent with the fact that childless women have similar employment rates across marital status. Utility from children is positive, but it decreases with the number of children. It also differs by marital status, where married women have the greatest utility. This is consistent with the fact that single women are less likely to have children. The parameters for occupation taste suggest that in order to match occupational sorting moments between real and simulated data, there has to be a high cost for working in professional occupations and a great benefit from working in services and clerical jobs. It is important to highlight that preference parameters will remain fixed for counterfactual exercises.

Table 1.6 shows estimated human capital parameters. Depreciation rates for both cognitive and social skills are small, but cognitive skills accumulate substantially over the life-cycle. In contrast, social skills have a very stable evolution, as noted in Lise and Postel-Vinay (2020). Experience accumulation is high for full-time work in the first stage of the life-cycle (ages 24-31), and double the experience accumulation for

[23] The variance matrix of the estimated parameters is $Var = [D'_m W D_m]^{-1} D'_m W S W' D_m [D'_m W D_m]^{-1}$, where D'_m is a 49*125 matrix of partial derivatives of moment conditions with respect to each parameter and S is the covariance matrix of data moments.

Table 1.5: Estimated Utility Parameters

Description	**Marital Status**	**Symbol**	**Estimate**	**Standard Error**
Part-Time	Married	$\gamma_1^{PT,\text{mar},\omega=2}$	-177.17	6.79
Full-Time	Married	$\gamma_1^{FT,\text{mar},\omega=2}$	-326.22	10.96
Part-Time*1 Child	Married	$\gamma_2^{PT,\text{mar},n=1}$	-5.00	5.41
Part-Time*2 Children	Married	$\gamma_2^{PT,\text{mar},n=2}$	-2.95	2.66
Part-Time*3 Children	Married	$\gamma_2^{PT,\text{mar},n=3}$	2.98	3.17
Full-Time*1 Child	Married	$\gamma_2^{FT,\text{mar},n=1}$	-5.02	5.90
Full-Time*2 Children	Married	$\gamma_2^{FT,\text{mar},n=2}$	-6.97	0.83
Full-Time*3 Children	Married	$\gamma_2^{FT,\text{mar},n=3}$	1.00	1.55
Part-Time	Single	$\gamma_1^{PT,\text{sin},\omega=2}$	-217.85	8.52
Full-Time	Single	$\gamma_1^{FT,\text{sin},\omega=2}$	-427.78	10.99
Part-Time*1 Child	Single	$\gamma_2^{PT,\text{sin},n=1}$	-1.99	3.73
Part-Time*2 Children	Single	$\gamma_2^{PT,\text{sin},n=2}$	-2.01	2.93
Part-Time*3 Children	Single	$\gamma_2^{PT,\text{sin},n=3}$	2.107	6.04
Full-Time*1 Child	Single	$\gamma_2^{FT,\text{sin},n=1}$	-5.01	36.2
Full-Time*2 Children	Single	$\gamma_2^{FT,\text{sin},n=2}$	-7.02	10.56
Full-Time*3 Children	Single	$\gamma_2^{FT,\text{sin},n=3}$	7.98	12.19
Part-Time, Type I	–	$\omega = 1$	-92.74	8.25
Part-Time, Type I	–	$\omega = 1$	-239.39	25.46
1 Child	Married	$\gamma_3^{\text{mar},n=1}$	279.43	3.36
2 Children	Married	$\gamma_3^{\text{mar},n=2}$	302.11	5.84
3 Children	Married	$\gamma_3^{\text{mar},n=3}$	302.64	5.51
1 Child	Single	$\gamma_3^{\text{sin},n=1}$	34.44	7.91
2 Children	Single	$\gamma_3^{\text{sin},n=2}$	19.95	10.54
3 Children	Single	$\gamma_3^{\text{sin},n=3}$	15.02	9.16
Manager/Professional	–	γ_1^{o}	-30.72	4.62
Health/Education	–	γ_2^{o}	125.03	6.14
Services	–	γ_3^{o}	165.49	6.28
Clerical	–	γ_4^{o}	162.95	6.41
Science	–	γ_5^{o}	77.27	6.07
Proportion Worker Type I (high disutility)	–	–	0.47	0.01
Scale Occupation Taste Shock	–	ν	9.70	0.97

Note: *Description* explains which parameter of the utility function is reported. *Marital Status* signals which parameters are marital status dependent. *Symbol* indicates the parameter symbol in the utility function. The superscripts PT and FT indicate part-time and full-time work; *mar* married and *sin* single; n number of children; ω preference for labor supply; and o occupation. *Estimate* indicates the point estimates for each parameter in the utility function. *Standard errors* are constructed with numerical gradient methods with a step-size equal to 1% of the parameter estimate value. I estimate the values for part-time and full-time unobserved cost in work for Type I and normalize to zero those for Type II.

Table 1.6: Estimated Human Capital Process Parameters

Description		**Symbol**	**Estimate**	**Standard Error**
Depreciation	x_c	δ_c	0.0024	0.00019
	x_s	δ_s	0.0018	0.00053
Accumulation	x_c	γ_c	0.0694	0.020
	x_s	γ_s	0.0030	0.004
Accumulation e	PT, 24-31	g(age,PT)	1.12	0.12
	PT, 32-39	g(age,PT)	0.25	0.08
	PT, 40-45	g(age,PT)	0.25	0.28
	FT, 24-31	g(age,FT)	2.14	0.18
	FT, 32-39	g(age,FT)	0.49	0.14
	FT, 40-45	g(age,FT)	0.46	0.77

Notes: *Description* explains which parameter of the human capital accumulation process is reported. Cognitive and social skills are represented by x_c and x_s, and experience by e. *Symbol* indicates the parameter symbol in the skills or experience accumulation functions. The subscripts s and c indicate social and cognitive skills; age the age groups [28-31], [32-39] and [40-45]; and *PT* and *FT* part-time and full-time work. *Estimate* indicates the point estimates for each parameter in the skills and experience accumulation functions. *Standard errors* are constructed with numerical gradient methods with a step-size equal to 1% of the parameter estimate value.

part-time work.

The wage parameters reported in Table 1.7 mirror the results from empirical wage regressions in Table 1.4.[24] The contributions of social and cognitive skills and occupational skill requirements to wages is positive, but it is higher in the cognitive dimension. The mismatch in the cognitive dimension is also negative, incentivizing workers to choose jobs which skill requirements are close to their own skills.

[24] Although similar, these are not the same. The reason is that the empirical wage regressions shown consider women in ages 24-36 (to make them comparable across cohorts) and the wage parameters of the model consider women in ages 24-45.

Table 1.7: Wage Parameters

Description	Symbol	Estimate	Standard Error
Constant	α_1	1.62	0.019
Cognitive Skills	α_2^c	0.34	0.022
Social Skills	α_2^s	0.18	0.017
Cognitive Requirements	α_3^c	0.79	0.035
Social Requirements	α_3^s	0.50	0.039
Mismatch cognitive	α_4^c	-0.22	0.039
Mismatch social	α_4^s	0.02	0.017
Experience	α_5	0.18	0.015

Note: *Description* explains which parameter of the wage function is reported. *Symbol* indicates the parameter symbol in the wage function. The subscripts s and c indicate social and cognitive skills. *Estimate* indicates the point estimates for each parameter in the wage function. *Standard errors* are constructed with numerical gradient methods with a step-size equal to 1% of the parameter estimate value.

Model Fit

Table 1.8 shows that the model performs well in fitting the shares of women out of work and in full-time work. The model also fits well the labor supply choices of married and single women. However, the model somewhat overpredicts a little the share of women in full-time work at the beginning of their working lives. Table 1.9 reports the fit for occupational choices and Table 1.10 the fit for the choice of children for women of different ages. Overall, the model does a good job at predicting the share of women across occupations. It underpredicts the share of childless women at the beginning of working life. Overall, it captures the timing of fertility over the life cycle very well.

The model also fits well moments initially not targeted, such as the marital wage gap, comparing wages of husband and wife. Table 1.11 shows the gender wage gap for all married women, those married to low educated husbands (LE) and those married to highly educated husbands (HE). Given that I did not specifically target wages by marital status in the estimation, the model is able to replicate the data moments very well. The average wage gap for married women in the data is 80%;

Table 1.8: Goodness of fit - Labor Supply

Description	Out of Work		Full-time		Out of Work	Full-time
	Data	Std. Err.	Data	Std. Err.	Simulated Data	
24-27	0.201	0.0013	0.567	0.0057	0.201	0.627
28-31	0.217	0.0013	0.517	0.0023	0.207	0.575
32-35	0.215	0.0013	0.487	0.0016	0.239	0.540
36-39	0.198	0.0014	0.487	0.0017	0.187	0.520
40-43	0.179	0.0013	0.525	0.0017	0.147	0.506
44-46	0.167	0.0014	0.542	0.0018	0.125	0.503
Single	0.119	0.0008	0.663	0.0014	0.105	0.696
Married	0.236	0.0007	0.446	0.0009	0.235	0.449

Note: *Data* indicates moments calculated from the sample of women in the 1960 cohort (CPS data). *Std. Err* reports bootstrapped standard errors for the data moments. *Simulated Data* shows the same moments from the sample simulated from the model.

Table 1.9: Goodness of fit - Occupation

Occupation	Data	Std. Err.	Simulated Data
Manager/Professional	0.180	0.0008	0.189
Health/Education	0.350	0.0011	0.355
Services	0.156	0.0008	0.156
Clerical	0.227	0.0009	0.227
Science	0.067	0.0006	0.072

Note: *Data* indicates moments calculated from the sample of women in the 1960 cohort (CPS data). *Std. Err* reports bootstrapped standard errors for the data moments. *Simulated Data* shows the same moments from the sample simulated from the model.

and the model produces a gap of 78%. It also captures differences in the wage gaps when considering education: a larger wage gap exists when the husband has high education and a lower gap exists when the husband has low education.

1.6 Accounting for Key Changes

The goal of this section is to measure the impact of two forces, changes in the labor market and changes in family formation, on the increase in women's participation in managerial, professional, education, and health-related jobs, on the increase in full-time work by women, and on the increase in the number of women who remain

Table 1.10: Goodness of fit - Children

Age	No Children			1 Child			2 Children			3 Children		
	Data	**S.E.**	**Sim.**	**Data**	**S.E.**	**Sim.**	**Data**	**S.E.**	**Sim.**	**Data**	**S.E.**	**Sim.**
24-31	0.580	0.016	0.465	0.200	0.012	0.229	0.155	0.012	0.221	0.061	0.012	0.079
32-35	0.341	0.016	0.385	0.206	0.013	0.182	0.292	0.015	0.274	0.161	0.014	0.158
36-39	0.267	0.015	0.342	0.185	0.013	0.162	0.342	0.016	0.305	0.206	0.014	0.189
40-43	0.247	0.016	0.320	0.179	0.014	0.153	0.352	0.016	0.328	0.221	0.015	0.197
44-46	0.244	0.010	0.315	0.172	0.008	0.148	0.354	0.017	0.336	0.230	0.013	0.199
Single	0.765	0.011	0.627	0.104	0.009	0.155	0.085	0.012	0.138	0.045	0.013	0.078
Married	0.249	0.008	0.216	0.238	0.008	0.197	0.333	0.005	0.381	0.179	0.005	0.205

Note: *Data* indicates moments calculated from the sample of women in the 1960 cohort (NLSY79 data). *S.E.* reports bootstrapped standard errors for the data moments. *Sim* shows the same moments from the sample simulated from the model.

Table 1.11: Marital Wage Gap

Description	Data	Sim
All Married	80%	78%
Married to LE Husband	91%	95%
Married to HE Husband	68%	67%

Note: *Data* indicates moments calculated from the sample of women of the 1960 cohort (NLSY79 data). *Sim* shows the same moments from the sample simulated from the model. *LE* indicates a low educated husband and *HE* a high educated husband.

childless by their mid-thirties.

Throughout this section I will present 'benchmark' results, which are labor supply, occupation and fertility choices predicted by the estimated model for the 1960 cohort. The simulations use the estimated parameters for the utility function and human capital accumulation process. In the counterfactuals, I will then allow for sequential changes in the initial distribution of skills and skill requirements, wage returns to different skills and skill requirements, transitions into and out of marriage, initial number of children and initial marital status.

The first counterfactual analyzes the contribution of changes in the wage structure, also accounting for changes in the initial distribution of workers' skills and in occupational skill requirements across cohorts. It keeps the initial number of children and marriage probabilities over the life-cycle unchanged. This exercise measures the contribution of the labor market channel. The second counterfactual evaluates the contribution of changes in marital status and number of children at the beginning of the working life, as well as changes in the marriage probability over the life-cycle across cohorts. It keeps the cognitive and social skills of women, skill requirements of occupations, and the wage structure unchanged. In this case, I measure the contribution of the family formation channel. As a final exercise, I evaluate the joint contribution of the two channels taken together in explaining changes in women's behavior.

1.6.1 Labor Market Channel

The question I want to answer with the first counterfactual is: To what degree are the key empirical changes due to changes in the wage structure, accounting for changes in the workers' initial skills and in occupational skill requirements across cohorts? I will disentangle the importance of each subcomponent when answering this question. In the counterfactual exercises, I set the model wage parameters so that the simulated wage regression parameters match the empirical regression parameters from Column (4) in Table 1.4 for the 1980 cohort, and the initial workers' skills and occupational skill requirements match those of the 1980 cohort.

The first outcome I study is occupational sorting. The wage evidence in Table 1.4 shows that the return to cognitive skill requirements increased from 0.73 to 1.27, and the return to social skill requirements increased from 0.43 to 1.25. This suggests that there are incentives to switch to occupations that are cognitive and socially intensive, such as managerial, professional, education and health-related jobs. This is what we observe in the first two columns of Table 1.12, which reports summary statistics from the data. The first column shows the share of women across occupations for the 1960 cohort and the second column for the 1980 cohort. There is an increase in the share of women in managerial and professional occupations (from 17% to 20%) and in health and education-related occupations (from 34% to 42%). At the same time, women leave clerical jobs, which have lower cognitive and social skill requirements (from 23% to 16%).

My model produces interesting results. In the third column, under the heading 'Estimation Benchmark', I report simulated moments for the estimated model for the 1960 cohort. In the fourth column, under the heading 'Labor Market', I show the share of women across occupations when I apply this first counterfactual scenario. It has a very high predictive power, as the share of women in managerial and professional jobs increases to 25.5% and in health and education to 45%. These shares are extremely close to the 1980 data, where 20% of women were in managerial and professional occupations and 42% in health and education jobs. This counterfactual also captures the decrease in employment in clerical jobs to 15%, very close to the 16% observed in the data. Although I overpredict the share of women in managerial, professional, health and education-related jobs, the results suggest that this counterfactual has an almost perfect fit for the purposes of occupational sorting.

In order to illuminate the contribution of each subcomponent of this counterfactual, I evaluate the response to changes in the wage structure, keeping the skill requirements of occupations and workers' skill requirements at the 1960 level. In this scenario, there is a huge increase of workers into health jobs, reaching 70%, leaving science and clerical jobs with very few women. Once I allow for occupational skill requirements to have the 1980 distribution, results resemble data patterns. The reason behind this change is that mean social skill requirements increased in science jobs and mean cognitive skill requirements increased in clerical jobs. As a result, the second factor (changes in distributions) counterbalances the strong effect from the first factor (changes in the wage structure). In a third step, I modify the distribution

Table 1.12: Share of Women across Occupations - Counterfactual Results

Occupation	Data Cohort 1960	Data Cohort 1980	Estimation Benchmark	Counterfactuals: Labor Market	Counterfactuals: Family	Counterfactuals: All Channels
	(1)	(2)	(3)	(4)	(5)	(6)
Manager/Professionals	17%	20%	18.9%	25.5%	20.8%	28.8%
Health/Education	34%	42%	35.5%	45%	36%	42.4%
Services	17%	17%	15.6%	5.6%	14.7%	5.5%
Clerical	23%	16%	22.7%	15.2%	21%	14.7%
Science	7%	6%	7.2%	8.7%	7.5%	8.6%

Note: *Data Cohort 1960* indicates the share of women across occupations calculated from the sample of women of the 1960 cohort (Source: CPS). In a similar way, *Data Cohort 1980* indicates data moments for the 1980 cohort (Source: CPS). *Estimation Benchmark* reports the share of women across occupations from simulated data, using estimated parameters for the 1960 cohort. *Counterfactual Labor Market* reports the share of women across occupations with the 1980 cohort's wage structure, workers' skills and occupational skill requirements. *Counterfactual Family* reports the same simulated moments with the 1980 cohort's marriage probabilities over the life-cycle, initial distribution of children and initial marital status. *Counterfactual All Channels* reports the same simulated moments incorporating *Counterfactual Labor Market* and *Counterfactual Family* together.

of workers' skills so that it matches that from the 1980 cohort. It is important to remember that although workers' skills are measured in percentile ranks, the correlations between cognitive and social skills could change over time, potentially leading to different results. I observe little impact of the shift in workers' skills distribution on occupational choice.[25]

I report the changes in full-time work and fertility under this counterfactual in Table 1.13. The first column of this table shows the share of women in full-time work, with no children and with two children in different age groups for the 1960 cohort. In the second column, I report the percentage change between the data moments of the 1980 cohort and the 1960 cohort. In the third column, I show the simulated moments for the estimated model for the 1960 cohort, and in the fourth column the percentage change between the counterfactual moments and benchmark simulated moments.

The first panel documents the results for full-time work. Column (4) shows that

[25] Results from counterfactuals switching off each of the three subcomponents (wages, occupations' skill requirements and workers' skills) are available upon request.

the share of women in full-time work under this counterfactual increased in comparison to the 'Estimation Benchmark', as the percentage change is around 10% for all age groups. Therefore, this counterfactual explains, on average, 56% of the changes in full-time employment.[26] In order to understand the mechanisms behind this change in behavior, I perform the following exercise: I keep the 1960 distribution of workers' skills and I set the wage structure and skill requirements of occupations to the values of the 1980 cohort. This is a useful exercise, given that changing the distribution of workers' skills didn't affect occupational sorting.[27] I observe that among women who change labor supply behavior and move into full-time work, approximately 80% are changing occupations and moving into managerial, professional, health and education-related jobs. Women in these occupations have higher wages and therefore incentives to work full time. Another channel that contributes to the changes in labor supply is the increase in returns to experience, from 0.037 to 0.041 in the wage regression (Table 1.4).

I also focus on fertility outcomes, especially at ages 36-39, where I observe the most important changes in the data across cohorts. This counterfactual generates an increase in the share of women with no children of 7.5% and a decrease in the share of women with two children of 5.4%. It explains 25% of the overall change in the share of women with no children and 25% of the change in the share of women with two children in this age group. To understand the mechanisms behind this decision, I perform the same exercise as with full-time work, changing the wage structure and occupational skill requirements, and keeping the distribution of workers' skills fixed. I find that more than 30% of women who decide to be childless are increasing the number of hours of work. This is consistent with the fact that in the model it is

[26] This is the result of the division of the percentage change I observe in simulation exercises and the percentage change I observe in data moments. Column (4) divided by Column (2).

[27] Keeping the workers' skills fixed allows identifying the workers who have incentives to switch behavior when I perform counterfactual exercises.

more costly to work longer hours if one has children. In addition, I find that the change in fertility we observe in Column (4) is mainly driven by women who change occupations towards managerial, professional, health and education-related jobs.

Table 1.13: Labor Supply and Fertility - Counterfactual Results

Age	**Data Cohort 1960**	**% Change Data 1960 - 1980**	**Estimation Benchmark**	**Counterfactuals** **% Change Labor Market**	**% Change Family**	**% Change All Channels**
	(1)	(2)	(3)	(4)	(5)	(6)
			Share of Women in Full-time Work			
24-27	55.7%	9.5%	62.7%	9.3%	3.5%	12.9%
28-31	51.6%	15.3%	57.5%	10.1%	3.6%	13.5%
32-35	48.7%	21.1%	54%	10%	2%	13.1%
36-39	48.7%	25.2%	51.9%	10.5%	3.5%	13.2%
			Share of Women with no children			
32-35	34.1%	14.3%	38.5%	6.2%	12.6%	20.4%
36-39	26.8%	30.5%	34.2%	7.5%	15.7%	24.7%
			Share of Women with 2 children			
32-35	29.2%	-13.7%	27.3%	-6.3%	-13.2%	-20.7%
36-39	34.2%	-21.6%	30.5%	-5.4%	-11%	-18.3%

Note: *Data Cohort 1960* indicates data moments calculated from the sample of women of the 1960 cohort. *% Change Data 1960-1980* shows the percentage change between the data moments of the 1960 and 1980 cohorts. *Estimation Benchmark* reports moments from simulated data, using estimated parameters for the 1960 cohort. *% Change Labor Market* shows the percentage change between the Estimation Benchmark and the results from a counterfactual with the 1980 cohort's wage structure, workers' skills and occupational skill requirements. *% Change Family* shows the percentage change between the Estimation Benchmark and the results from a counterfactual with the 1980 cohort's marriage probabilities over the life-cycle, initial distribution of children and initial marital status. *% Change All Channels* shows the percentage change between the Estimation Benchmark and the results from a counterfactual with the Labor Market and Family channels.

1.6.2 Family channel

In this subsection, the aim is to explain the degree to which key empirical changes are due to changes in marriage probabilities over the life cycle, in the initial distribution of children and in the initial marital status across cohorts. As shown in Figure 1.3, women born in the 1960s were more likely to be married, both to highly educated and low educated husbands, than their counterparts from the 1980s. I estimate the probabilities of a partner arriving and leaving by age for the 1980 cohort using a logistic regression. In addition, at the initial age in the model's life cycle, the share of women with no children was 52% for the 1960 cohort, in comparison to 57% for the 1980 cohort.

The results of occupational sorting appear in Column (5) of Table 1.12 under the heading 'Family'. This counterfactual has little predictive power for the changes in occupation choices of women across cohorts. It seems that the main driver is the variation in the wage structure, which in this counterfactual is kept constant. Changes in family formation do affect women's decisions regarding labor supply, reported in Column (5) of Table 1.13. In this case, we observe an increase in full-time work of 3.5% among all age groups, which represents 18% of the overall change we observe in the data. The changes in marital status across cohorts increase the proportion of single women, which translates into different consumption equivalence scales at the household level. In this particular model, it would imply a reduction from a scale of 2 to 1.4 if a woman is a mother and from 1.6 to 1 if a woman does not have children. In both cases, although preferences for work change slightly across marital status, women have an incentive to move towards more hours of work.[28]

Regarding fertility decisions, the results are displayed in Column (5) of Table 1.13 in the second and third panels. This counterfactual generates an increase in the share of childless women in the age group 36-39 of 15.7%, which represents 51% of the total variation observed in the data. In addition, it generates a fall in the share of women with two children in the same age group of 11%, which is around 50% of the observed change between the 1960 and 1980 cohorts. The change in behavior is promoted by the change in the consumption equivalents, as the decision to have a child is more expensive when one is single.[29] In addition, there is a link between labor supply and

[28]I am working on an extension of this model where I allow the utility from consumption to interact with each of the work choices. If there is a negative interaction between the utility from consumption and labor supply, as in Edwards (2014), a smaller income due to a husband's absence will lead to an increase in labor supply. My estimates, in the current case, would underestimate the potential explanatory power of the family channel.

[29]The variation in eq if the woman is single is from 1.4 to 1 (child vs. no child) and if the woman

fertility choices, as working longer hours and having children is more expensive. In this counterfactual exercise, I look at those individuals in simulations who changed fertility behavior and I find that over 70% of those who decide to not have children are working longer hours.

I am aware that some of the results, in particular fertility patterns, may be affected by the initial distribution of children, which changes across cohorts. And given that fertility is an endogenous choice, the initial distribution can be affected by changes in labor market dynamics or marital status over time. Hence, I perform a counterfactual where I vary the probabilities of a partner arriving and leaving by age and initial marital status, but I keep the 1960 cohort's initial distribution of children. The changes in fertility patterns over time are almost the same as in Column (5) of Table 1.13, where, for example, the share of women aged 36-39 with two children declines by 9% (in comparison to 11% under the full counterfactual).[30]

1.6.3 Labor Market and Family Channels Taken Together

In this subsection, I report the results from incorporating the two channels. This involves introducing changes across cohorts in the wage structure, in workers' initial skills, in skill requirements of occupations, in marriage probabilities over the life cycle, in the initial distribution of children, and in the initial marital status.

The results for occupational sorting are displayed in Column (6) of Table 1.12. Although I over predict the share of women in manager, professional, health and education-related jobs, I am able to explain the main patterns in the data. By comparing the results from Columns (4), (5) and (6), it is clear that the main driver of the changes in occupational sorting is the labor market, with few changes arising

is married is from 2 to 1.6 (child vs. no child).

[30]Results from this counterfactual where I keep the initial distribution of children fixed at the values of the 1960 cohort are available upon request.

from family formation. Looking at full-time work results in Column (6) of Table 1.13, the channels taken together are able to generate an increase in full-time work, which represents on average 74% of the overall variation observed in the data. Both labor market and family forces are important in explaining full-time work changes, but the former has a higher impact.

Regarding fertility patterns, I find that at the ages of 36 to 39, this counterfactual explains 81% of the increase in the share of women who are childless and 85% of the change in the share of women with two children across cohorts. Comparing Columns (4) and (5) in Table 1.12, we notice that the family channel plays a more important role in fertility choices than the labor market one.

1.7 Conclusion

In this paper, I develop a life-cycle model to explain the changes in highly educated women's labor market and fertility behavior across cohorts. The model includes three key choices: labor supply, occupation, and fertility. I estimate the model for the 1960 cohort and analyze the relative contribution of two forces to explain the patterns in the data. The first force is a change in the labor market, which incorporates changes in the wage structure, in the initial distribution of workers' skills and in the skill requirements of occupations across cohorts. The second force involves changes in family formation, which includes changes in marriage probabilities over the life cycle, in the initial distribution of children and in initial marital status across cohorts. I call these forces 'Labor market' and 'Family', respectively.

I find that the labor market channel has a large impact on occupation and full-time work choices. More concretely, this channel explains almost perfectly the changes in occupational sorting, which involve the increase in the share of women employed in managerial, professional, health and education-related jobs and the decrease in their involvement in clerical jobs. It also explains 56% of the changes in full-time employment, arising from changes in occupational choice and the increase in the returns to experience. This channel also explains 25% of the increase in the share of women with no children across cohorts.

The family channel has a large impact on the decision to have children and on labor supply, but has negligible effects on occupational sorting. It explains 18% of the observed increase in full-time work across cohorts, 51% of the increase in the share of women who have no children, and 50% of the decrease in the share of women with two children.

Overall, both channels are needed to explain the observed changes. Although these two forces overpredict the increase in employment in managerial, professional, health and education-related jobs, the direction of the change and magnitudes are very aligned with observed changes. In addition, together they explain 74% of the increase in full-time work, 81% of the increase in the share of women with no children, and 85% of the decrease in the share of women with two children. Hence, these two forces are necessary to explain the changes in behavior between the 1960 and 1980 cohorts.

Throughout my analysis I keep preferences fixed across cohorts, so it may be possible that the unexplained share of change in behavior could be explained by other factors such as changes in social norms. There is a growing number of papers that highlight the importance of social norms in labor supply decisions (Fernández, Fogli, and Olivetti (2004), Fernández (2013), Bertrand, Kamenica, and Pan (2015), Goussé, Jacquemet, and Robin (2017)) that I could introduce through changes in preferences for labor supply across cohorts.[31] Another extension of my model would

[31]NLSY79 and NLSY79 Young Adults provide eight statements that address attitudes on gender

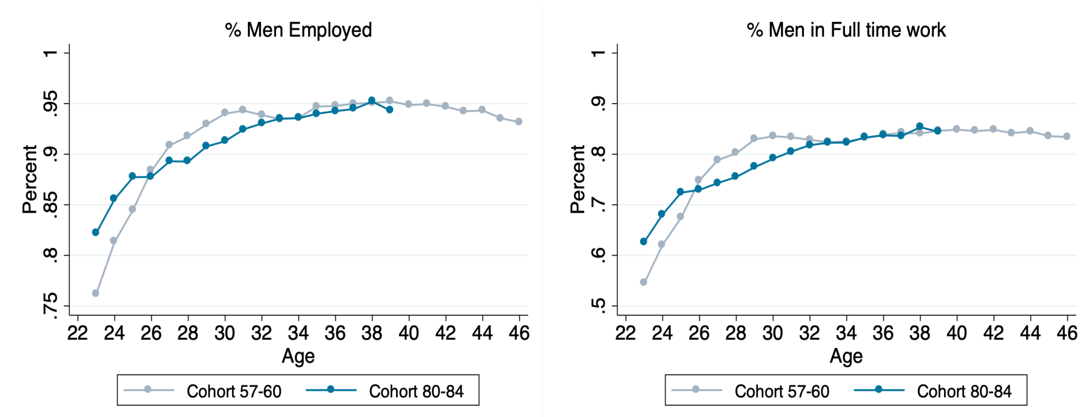
include an endogenous decision of marriage, within an equilibrium life-cycle model as in Chiappori, Dias, and Meghir (2018) and Reynoso (2019). Such changes in the structure of wages across cohorts may have implications for family formation that were beyond the scope of the current paper, but that could explain changing marriage patterns. In addition, a future avenue of research could incorporate equilibrium in both the labor market and the marriage market within a life-cycle framework.

roles regarding employment. Women need to indicate whether they agree or disagree with them. These include, among others, that the place for a woman is the home and not an office, that a wife who has full family responsibilities does not have time for outside employment and that women are much happier if they stay home taking care of children. Labor supply decisions would depend on social norms in an extended version of this model.

1.8 Appendix

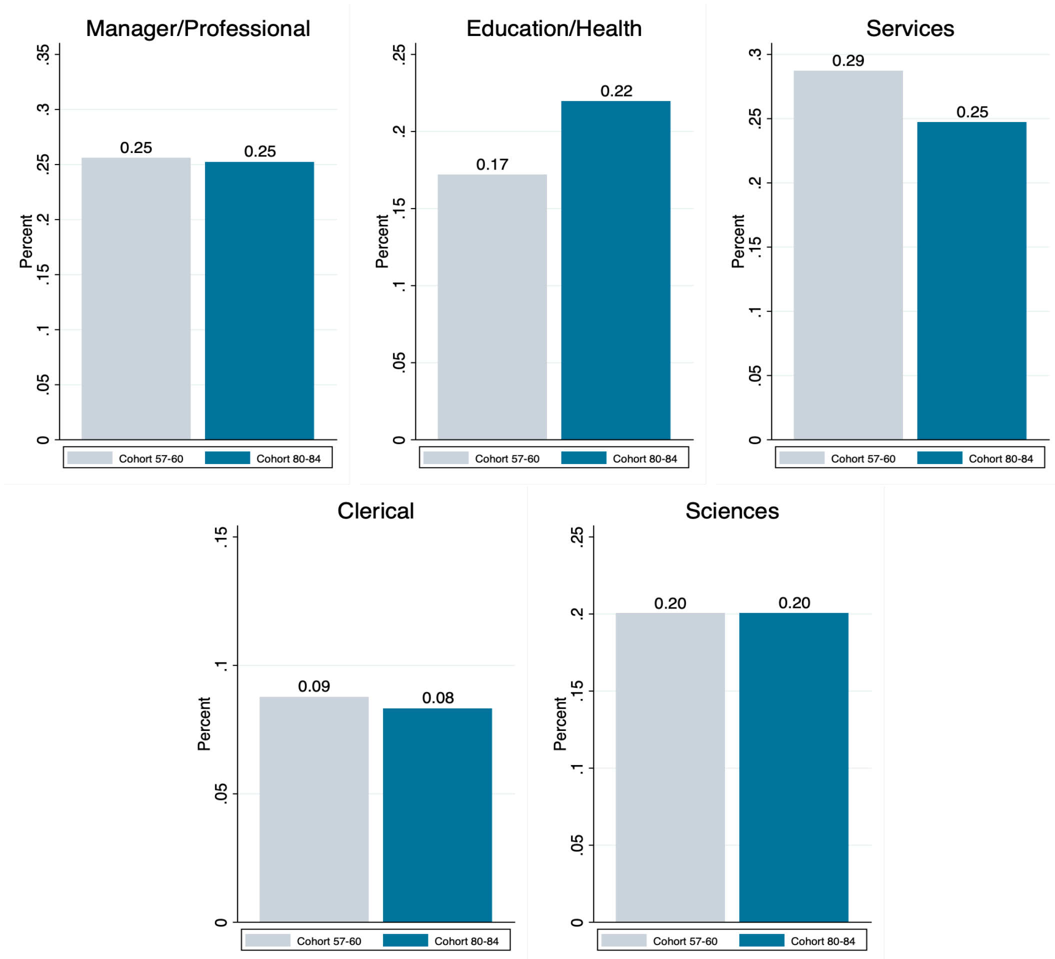
1.8.1 Labor Supply and Wages of Men

Figure 1.6: Labor Supply of Highly Educated Men



Note: CPS data. Employment and Full-time work of highly educated men, for 1956-1960 and 1980-1984 cohorts. Full-time workers are defined as those individuals working more than 35 hours per week.

Figure 1.7: Occupational Choices of Highly Educated Men



Note: CPS data. Employment and Full-time work of highly educated men, for 1956-1960 and 1980-1984 cohorts. Full-time workers are defined as those individuals working more than 35 hours per week.

Table 1.14: Regression of Husband's ln Wages by Education Level

	(1) >HS	(2) <=HS
Age	0.152***	0.077***
	(0.0165)	(0.0132)
Age sq.	-0.002***	-0.001***
	(0.000250)	(0.000199)
Constant	0.0882	1.252***
	(0.291)	(0.234)
N	15,056	18,844

Note: Data from NLSY79. The dependent variable is ln wages of husbands. Wages are in 2016 constant dollars, and I trim values of the real hourly wage that are below 3 and above 200. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

1.8.2 Female Wages

Table 1.15: Regression of Female ln Wages

	(1) Cohort 1960	(2) Cohort 1980	(3) Cohort 1960	(4) Cohort 1980	(5) Cohort 1960	(6) Cohort 1980
Cognitive Skills x_c	0.485***	0.411***	0.507***	0.381***	0.459***	0.352***
	(0.0329)	(0.0359)	(0.0556)	(0.0582)	(0.101)	(0.0980)
Social Skills x_s	0.200***	0.143***	0.165***	0.170***	0.150	0.0345
	(0.0335)	(0.0344)	(0.0520)	(0.0586)	(0.0958)	(0.102)
Cognitive Requirement y_c			0.639***	1.145***	0.732***	1.174***
			(0.0677)	(0.0822)	(0.125)	(0.128)
Social Requirement y_s			0.489***	1.167***	0.597***	1.439***
			(0.0629)	(0.0861)	(0.123)	(0.136)
Overqualified Cog. $x_c - y_c$			-0.320***	-0.250**		
			(0.101)	(0.109)		
Overqualified Soc. $x_c - y_c$			0.0363	-0.157		
			(0.0881)	(0.102)		
Experience			0.0376***	0.0406***	0.0377***	0.0402***
			(0.00155)	(0.00178)	(0.00191)	(0.00201)
$\max\{x_c - y_c, 0\}^2$					-0.542*	-0.566**
					(0.290)	(0.286)
$\min\{x_c - y_c, 0\}^2$					-0.224	-0.0199
					(0.226)	(0.188)
$\max\{x_s - y_s, 0\}^2$					0.141	0.0652
					(0.231)	(0.252)
$\min\{x_s - y_s 0\}^2$					-0.0208	-0.238
					(0.194)	(0.227)
Constant	2.351***	2.484***	1.528***	1.031***	1.443***	0.946***
	(0.0219)	(0.0256)	(0.0414)	(0.0640)	(0.0484)	(0.0716)
Observations	15868	15765	14989	15302	14989	15302

Note: Data from NLSY79 and NLSY97. Columns (1) and (2) report coefficients of a regression of ln wages on cognitive and social skills, for cohorts 1960 and 1980. Columns (3) and (4) include in the regression cognitive and social skill requirements, experience, and mismatch for overqualification. The latter is a variable that is 0 for underqualification and $x_c - y_c$ for overqualification in the cognitive dimension. Analogous for social skills. Columns (5) and (6) report results from a regression where I include social and cognitive skills and skill requirements, experience, and mismatch for over- and underqualification in a quadratic manner. Wages are in 2016 constant dollars, and I trim values of the real hourly wage that are below 3 and above 200. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

1.8.3 Principal Component Analysis

In this section, I report results from the principal component analysis. I take the first principal component for the cognitive and social dimensions. In the case of the cognitive dimension, the first component explains 64% and 63% of the total variance for the 1960 and 1980 cohorts, respectively. In the social dimension, the first component explains 70% and 66%, respectively. I now report the loadings for each of the descriptors included in the analysis.

Table 1.16: Loadings for O*NET descriptors

Description	**Cohort 1960**	**Cohort 1980**
Mathematical Reasoning	0.618	0.597
Number Facility	0.592	0.527
Memorization	0.156	0.143
Reading Comprehension	0.245	0.277
Mathematics	0.503	0.517
Social Perceptiveness	0.485	0.492
Contact with others	-0.125	-0.155
Assisting and caring for others	0.571	0.565
Service orientation	0.464	0.461
Personal Services	0.454	0.448

Notes: O*NET data. Loadings from principal component analysis.

1.8.4 List and Description of Moments

Table 1.17: List and description of moments

Description	Conditioning	Count
Work choices and dynamics of labor supply		
% in FT, Out of Work	Age, Marital Status	16
% in each occupation	–	5
% in FT, Out of Work	Number of Children, Marital Status	18
% in FT, Out of Work	Infant Kid, Marital Status	6
Fertility		
% women with 0,1,2 and 3 children	Age	24
% women with 0,1,2 and 3 children	Marital Status	8
Wages		
Mean of ln wages	Age	6
Coeff. of ln wage regression	–	8
Human Capital Accumulation		
Mean wage increase from t to $t+1$	$x_t y_t$	2
Mean wage increase from t to $t+1$	FT & PT in t	8
Mean wage increase from t to $t+1$	experience in t	8
Mean y	working & after period not working	4
Transitions		
PT, FT, Out of Work	–	11
Occupations	–	5

Note: (i) Age is grouped into six bands [24-27], [28-31], [32-35], [36-39], [40-43], [44-46]; (ii) x denotes worker skills and y occupational skill requirements; (iii) data from CPS and NLSY79.

1.8.5 Goodness of fit

In this section I report the goodness of fit for moments targeted in the estimation.

Table 1.18: Goodness of fit: Mean ln Wages

Description	ln **Wages**		
	Data	**S.E.**	**Sim. Data**
24-27	2.62	0.012	2.63
28-31	2.85	0.011	2.82
32-35	2.90	0.015	2.89
36-39	2.99	0.017	2.88
40-43	3.01	0.021	2.89
44-46	2.79	0.024	2.92

Note: *Data* indicates moments calculated from the sample of women in the 1960 cohort (NLSY79 data). *S.E.* reports bootstrapped standard errors for the data moments. *Sim. Data* shows the same moments from the sample simulated from the model.

Table 1.19: Goodness of fit: Regression ln Wages

Description	**Regression** ln **Wages**		
	Data	**S.E.**	**Sim. Data**
x_c	0.33	0.041	0.31
x_s	0.16	0.035	0.18
y_c	0.73	0.034	0.81
y_s	0.43	0.056	0.45
$\|x_c - y_c\|$	-0.17	0.057	-0.16
$\|x_s - y_s\|$	0.007	0.060	0.002
Experience	0.038	0.048	0.04
Constant	1.66	0.009	1.65

Note: *Data* indicates moments calculated from the sample of women in the 1960 cohort (NLSY79 data). *S.E.* reports bootstrapped standard errors for the data moments. *Sim. Data* shows the same moments from the sample simulated from the model.

Table 1.20: Goodness of fit: Human Capital Accumulation

Description	**Human Capital Accumulation**		
	Data	**S.E.**	**Sim. Data**
Reg. ln wages on ln exp (1st diff.)	0.28	0.014	0.31
Mean wage increase if FT in $t-1$	0.043	0.0052	0.049
Mean wage increase if PT in $t-1$	0.033	0.0116	0.036
Mean y_c if working	0.49	0.005	0.51
Mean y_c after period out of work	0.46	0.009	0.50
Mean y_s if working	0.49	0.005	0.54
Mean y_s after period out of work	0.49	0.012	0.52
Mean wage increase with $x_c y_c$ in $t-1$	0.13	0.011	0.08
Mean wage increase with $x_s y_s$ in $t-1$	0.09	0.016	0.11

Note: *Data* indicates moments calculated from the sample of women in the 1960 cohort (NLSY79 data). *S.E.* reports bootstrapped standard errors for the data moments. *Sim. Data* shows the same moments from the sample simulated from the model.

Table 1.21: Goodness of fit: Transitions

Description	**Transitions**		
	Data	**S.E.**	**Sim. Data**
Out of Work - Employed	0.39	0.009	0.26
Employed - Out of Work	0.12	0.004	0.07
Man/Prof (stayer)	0.63	0.014	0.83
Health (stayer)	0.58	0.032	0.27
Services (stayer)	0.82	0.008	0.62
Clerical (stayer)	0.57	0.012	0.29
Science (stayer)	0.65	0.011	0.37

Note: *Data* indicates moments calculated from the sample of women in the 1960 cohort (NLSY79 data). *S.E.* reports bootstrapped standard errors for the data moments. *Sim. Data* shows the same moments from the sample simulated from the model.

Table 1.22: Goodness of fit: Children and Labor Supply

Description	**Transitions**		
	Data	**S.E.**	**Sim. Data**
Out of Work - 1 Child	0.28	0.015	0.26
FT - 1 Child	0.52	0.018	0.46
Out of Work - 2 Children	0.39	0.016	0.38
FT - 2 Children	0.35	0.018	0.31
Out of Work - 3 Children	0.39	0.026	0.21
FT - 3 Children	0.34	0.024	0.60

Note: *Data* indicates moments calculated from the sample of women in the 1960 cohort (NLSY79 data). *S.E.* reports bootstrapped standard errors for the data moments. *Sim. Data* shows the same moments from the sample simulated from the model.

Chapter 2

Women, Fertility and Informality

(Joint with Lucas Finamor and Boryana Ilieva)[1]

2.1 Introduction

Recent empirical literature provides solid evidence on the relationship between female labor market outcomes, gender norms and fertility decisions. Women are more likely to drop out of the labor force after the birth of the first child, work part-time, and move to self-employment (Blau and Kahn (2007), Lim (2017), Kuziemko, Pan, Shen, and Washington (2018), Kleven, Landais, Posch, Steinhauer, and Zweimüller (2019a), Kleven, Landais, and Søgaard (2019b), Berniell, Berniell, De la Mata, Edo, and Marchionni (2021)). In addition, the event of childbirth is also highly correlated with the widening of the gender wage gap (Goldin, 2014).

Much of the evidence comes from developed and high income countries, but less is known about the relationship between fertility and labor market outcomes in developing countries (Cruces and Galiani (2007), Agüero and Marks (2008), Berniell,

[1]This research uses information from the Social Protection Survey (Encuesta de Protección Social). We thank the Sub-secretary of Social Protection, the intellectual owner of the survey, for the authorization to use the innominate datset. All the results from this research are responsibility of the authors and do not correspond to those of the Chilean Sub-secretary of Social Protection.

Berniell, De la Mata, Edo, and Marchionni (2021)). The labor markets in Latin American countries differ greatly from high income countries. First, the formal sector is much more rigid, allowing for less flexibility in working arrangements, such as hours and place of work. Second, informality is widespread. According to Maloney (2004), between 30% and 70% of the urban work force in Latin American countries is informal. The definition of informality varies among existing studies, but it usually subsumes wage earners without a labor contract and other workers with low social security contributions, such as the self-employed. Informal workers are considerably more exposed to risk not only because they are in sectors with higher earnings volatility and turnover, but also due to the lack of access to social insurance programs such as unemployment benefits, disability insurance, pensions, and maternity leave in the case of women. We use Chile as a case study, because the availability of its rich data sets allows us to employ panel data and perform event studies as our empirical strategy. Even though informality rates in Chile are lower than in other Latin American countries, our results could be informative for developing countries with similar labor market characteristics. Finally, formal childcare is still largely unavailable (Mateo Díaz and Rodriguez-Chamussy, 2016), so the presence of children can be expected to have a strong effect on the labor supply of women in the household.

In this paper, we distinguish three sectors of employment: formal, informal and self-employment. We define a formal worker as one that has a defined labor contract. A written labor contract protects against unexpected events like unemployment and ensures benefits such as social security and labor union participation rights. An informal worker, however, is not in possession of such a contract and a self-employed individual works independently. We show that these sectors differ in hours of work, workplace flexibility, wages, firm size, and occupation composition.

We begin our event studies analysis by documenting well-known facts, such as the fall in labor force participation and wages of women after the birth of the first child, in comparison to men (Kuziemko, Pan, Shen, and Washington (2018), Kleven, Landais, Posch, Steinhauer, and Zweimüller (2019a), Kleven, Landais, and Søgaard (2019b), Berniell, Berniell, De la Mata, Edo, and Marchionni (2021)). We evaluate whether occupational sorting is behind the fall in wages of women after childbirth. We find that there is a positive association between cognitive skill requirements and wages and that there is a fall in the cognitive skill requirements of the occupations in which women are employed after childbirth.[2] We also analyze the choice of sector of employment. As in previous literature, we find that there is a fall in formal work.[3] We bring insights into the choice of informal work and self-employment. We find that there are no significant changes in the share workers in the informal sector after childbirth for both men and women. In addition, we find that women are more likely to switch into self-employment after childbirth and that the effect is larger for highly educated women (those that have more than high school education). Overall, we observe a decrease in formal work, no changes in informal work and an increase in self-employment, all conditional on employment. These results are exactly aligned with the degree of flexibility of these sectors, where formal work and self-employment are at the opposite ends of the spectrum. We also observe that flexible arrangements differ by education level: while highly educated women are more likely to work remotely and keep their hours of work unchanged after childbirth, lower educated women remain working at the firm and reduce their hours of work.

In addition, we analyze insurance decisions of men and women regarding pension

[2]Cognitive skill requirements are measured as required cognitive tasks at the occupational level. More details in Section 2.3.

[3]Our definition of informal employment considers workers who do not have a labor contract and differs from other definitions in the literature. More concretely, Berniell, Berniell, De la Mata, Edo, and Marchionni (2021) consider workers who share at least one of these characteristics: do not contribute to social security, do not have a labor contract, are self-employed and low-educated, and have temporary jobs.

contributions and type of health coverage. We observe a fall in female contributions to the pension system relative to men, where married women experience the largest fall. This different behavior by marital status may have long-run welfare implications in the case of divorce. In relation to health coverage, we find that women are less likely to keep private insurance after childbirth, while men experience no effects. This may be related to poorer economic conditions, as women are more likely to leave the labor force after childbirth.

In a final exercise, we explore the effects of the 2008 Chilean pension system reform, which aimed to decrease the gender gap in pensions in two ways: (i) through government coverage of women's pension contribution for each child born alive (an amount of 10% of 18 minimum wages) and (ii) in case of divorce, a judge can determine that a spouse keeps up to 50% of the other spouse's pension funds accumulated during marriage. We study the impact of the reform on formal employment and observe that women who had children after the reform are less likely to leave formal employment, in comparison to those who had children before 2008.

This paper is structured as follows. In Section 2.2 we summarize the main findings in the literature and our main contribution. In Section 2.3 we introduce the data sets and display important descriptive statistics of the sample. In Section 2.4 we introduce our empirical strategy. In Section 2.5 we present our results. In the final section we conclude.

2.2 Related Literature and Contribution

This paper contributes to three strands of the literature: (i) research on gender gaps in the labor market and their determinants, (ii) studies on informality and choice of sectors of employment, and (iii) work that explores the effects of the 2008 Chilean pension system reform.

Several studies have documented that the gender wage gap in developed countries has decreased over the period 1970-1990, but its closing has had a slower rate in the last three decades (Goldin (2006), Blau and Kahn (2006), Blau and Kahn (2007), Blau and Kahn (2017)). The narrowing of the gap has been mainly driven by an increase in human capital accumulation and labor market attachment among females, as well as by a decrease in occupational segregation by gender (Blau and Kahn, 2017). As children remain the primary reason for women to change career plans and are a major driver of the gender wage gap (Goldin (2006), Correll, Benard, and Paik (2007), Bertrand, Goldin, and Katz (2010)), our paper studies gender gaps in labor market outcomes and insurance decisions around the time of childbirth focusing on a developing context.

Like previous related literature (Kuziemko, Pan, Shen, and Washington (2018), Kleven, Landais, Posch, Steinhauer, and Zweimüller (2019a), Kleven, Landais, and Søgaard (2019b), Berniell, Berniell, De la Mata, Edo, and Marchionni (2021)), we use an event study approach to study the gender gaps around the time of childbirth.[4] These papers find that there is an increase in the gender gap in earnings, a decrease in labor force participation and wages of mothers relative to fathers, and that many of these effects are persistent. We investigate if the wage decrease after childbirth is related to different occupational choices. More concretely, we study the cognitive content of occupations in which women are employed before and after childbirth.

This paper also relates to studies that analyze how workers choose sectors of employment, especially in developing countries (Dix-Carneiro and Kovak (2019), Dix-Carneiro, Goldberg, Meghir, and Ulyssea (2019), Berniell, Berniell, De la Mata,

[4]In reference to methodology, our paper addresses the issues of non-convex weighting when using two-way fixed effect estimators in event studies with varying treatment timing, typically not addressed in the literature, by following the method implemented in Sun and Abraham (2020).

Edo, and Marchionni (2021), Ponczek and Ulyssea (2020)). Our paper distinguishes multiple characteristics of each job and classifies individuals as formally employed, informally employed, or self-employed — three coexisting types of employment typically found in developing countries. We define formal workers as individuals in possession of a defined labor contract. A written labor contract protects against unexpected events such as lay-offs on short notice and ensures entitlement to benefits such as social security and labor union participation rights. Informal workers, in contrast, are not in possession of such a labor contract. Self-employed individuals work independently. In the context of developing countries, accounting for self-employment is important since a nontrivial fraction of the working population has neither a formal nor an informal employer. Jobs in these three sectors of employment also differ in characteristics, such as hours and place of work, 'firm' size, wages, cognitive skill requirements and the share of people that contributes to the pension system. The percentage of individuals that contribute to the pension system is above 98% in the formal sector, around 20% in the informal sector and 16% for those in self-employment. Contrary to other approaches in the existing literature, we acknowledge that workers could contribute to the pension system while being self-employed or working without a labor contract.

As we measure different characteristics of jobs, which include hours of work and work location, we contribute to the literature on child penalties and the search of flexible work arrangements (Golden (2001), Golden (2008), Goldin and Katz (2011), Edwards (2014), Goldin (2014)). While there is significant literature studying the choice of part-time work, we bring a less explored dimension, which is workplace flexibility. In the Chilean context, the formal sector is the most rigid, where more than 80% of women work at the establishment. The informal sector is still very inflexible in place of work, as around 40% of women work at the firm. In self-employment, however, less than 20% of workers work at the firm site.

While clearly related in spirit, the recent paper by Berniell, Berniell, De la Mata, Edo, and Marchionni (2021) differs from ours in several ways. First, their definition of informality differs from ours, subsuming workers in at least one of the following categories: not contributing to social security, low-skilled in self-employment, working with no labor contract and having a temporary job.[5] Second, we consider self-employment as a different sector of employment, as it is characterized, for example, by different work arrangements and wage distribution. Third, we study occupational sorting, workplace flexibility, health insurance, the effects of the pension reform, among other outcomes, not addressed in their paper.[6]

We further analyze gender gaps in health and social security insurance after the birth of the first child. While there is some evidence that women are less likely to contribute to the pension system after the event of childbirth (Subsecretaría de Previsión Social (2015), Amarante, Colacce, and Manzi (2017), Berniell, Berniell, De la Mata, Edo, and Marchionni (2021)), we additionally explore differences by marital status, providing insights on the source of the pension gender gap. On the health dimension, we study whether women differently change their health insurance rates and association with a private health care provider after childbirth.

Finally, we study the implications of the 2008 pension system reform on labor force participation and formal employment of men and women in Chile. We perform event studies on men and women who gave birth before and after 2008 to study the effects of the reform, complementing the existing literature exploring the effects of the reform on pension wealth, formal employment, pension contributions, among other outcomes (Attanasio, Meghir, and Otero (2011), Behrman, Calderon, Mitchell,

[5]In a previous version of their paper, they considered an informal worker an individual who did not contribute to the social security system.

[6]Their paper differs from ours as well in methodology and sample selection, as ours considers individuals who became parents between 1981 and 2016 and theirs between 2002 and 2015.

Vasquez, and Bravo (2011), Todd and Joubert (2013)).

2.3 Data and Institutional Setting

Our main dataset is a longitudinal survey from Chile, "*Encuesta de Protección Social*" (EPS).[7] The survey has six waves (2002, 2004, 2006, 2009, 2012 and 2015) and contains, among others, information on demographics, family structure, health, earnings, employment, and wealth, where almost 35,000 individuals are interviewed.[8] Labor market spells are characterized by information on the contractual relationship, firm size, hours of work, occupation and industry. Historical information dating back to 1980 is obtained in the first interview. In each survey wave, labor market information and changes in the family structure since the last interview are recorded. Information on other variables, such as wealth, is available only for the years in which individuals were surveyed. Wages are available for all spells from the year 2002 onward and detailed labor market trajectories can be reconstructed for the majority of the workers. The resulting 35-year panel allows us to analyze the allocation of the labor force in different sectors of employment and its relation to a child arrival, conditional on various socio-demographic characteristics. Since this data can be linked to the administrative data on the Pension System in Chile, "*Historia Previsional de Afiliados*" (HPA), on some occasions, we use the administrative records to minimize measurement error.

In addition to the above data sets, we use the Occupation and Information Network data set (O*NET) to build a measure of cognitive skill requirement of occupations.[9] This data set contains information on a wide array of requirements at the

[7] Ministry of Labor and Social Protection, Survey EPS.

[8] Since the second wave, the EPS is a nationally representative survey of the Chilean population.

[9] This data set is developed under the sponsorship of the U.S. Department of Labor/Employment and Training Administration.

occupational level, such as abilities, knowledge, skills, and work styles. We use 18 descriptors of core cognitive tasks, perform principal component analysis and keep the first principal component as a measure of cognitive skill requirements at the occupational level. We normalize the score to be in the interval [0,1].

2.3.1 Sample

For the purpose of this study, we consider the time period 1981-2016 and individuals born between 1945 and 1995, aged between 16 and 59.[10] As we are interested in the way in which a child arrival shapes individuals' careers, we focus on individuals who become parents at some point during the observation period. Table 2.1 below presents key descriptive statistics of our sample of interest, which contains 6,729 mothers and 6,045 fathers. We observe that around two thirds of women have a high school degree at most, while the remaining third has a higher education level (some college, college degree or more). In the case of men, around 30% have higher education. We also explore family related statistics, and report that 75.6% of women and 86.3% of men were married at childbirth. The average age at first birth is around 23 and 25 for women and men, respectively. Individuals can be observed for around 25 years on average.

2.3.2 Labor Market Characteristics

In Table 2.2 we present a summary of the information related to the labor market. We converted the spell information to a monthly panel given that this is the most desegregated information from the spell reporting.[11] We report working hours and wages after removing the highest and lowest 2% of observations. We observe that men work more hours than women, 48.4 weekly hours versus 45, respectively. Wage

[10]We limited the maximum age to 59 because 60 is the legal retirement age for women in Chile.

[11]As we discuss in section 2.4, the event studies will use monthly data but the event dummies are coded annually.

Table 2.1: Descriptive Statistics

Statistic	**N**	**Mean**	**St. Dev.**
Panel A — Women			
Cohort	6,729	1974	11.892
Less than high school	6,729	0.140	0.347
High school degree	6,729	0.526	0.499
More than high school	6,729	0.334	0.472
Marital status	6,729	0.756	0.429
Age at birth of first child	6,729	23.801	5.081
Years observed	6,729	24.859	10.078
Panel B — Men			
Cohort	6,045	1 971	11.775
Less than high school	6,045	0.178	0.382
High school degree	6,045	0.534	0.499
More than high school	6,045	0.289	0.453
Marital status	6,045	0.863	0.344
Age at birth of first child	6,045	25.541	5.285
Years observed	6,045	26.860	9.449

Note: Data from EPS. Cohorts born between 1945 and 1995, individuals ages 16 and 59. Columns report *Number of Observations* (N), *Mean* and *Standard Deviation* (St.Dev.). Panel A presents the statistics for Women and Panel B for Men.

information is reported as the logarithm of monthly wages in Chilean UFs, which corresponds to, approximately, 40 USD. Wages for men in the sample are higher than wages for women. On average, the wage measure for women is 2.38, while the male average stands at 2.61.

Table 2.2 further summarizes the rates of labor force participation, employment in different sectors as well as ratios of employment by type of working arrangement. Average labor force participation is 57% for women and 88.8% for men. Unemployment rates are higher among females: only 4.5% of men are unemployed while 8% of women are unemployed. Employed individuals work in four main sectors: the public sector, the formal sector, the informal sector, and self-employment. Informal workers are those that work for private firms but report that they do not have a signed labor contract. Self-employed individuals are those that declare to work independently (*cuenta propria*). Following these definitions, participation of men in the formal sector conditional on participation is 59%, in the informal sector is 8% and in self-employment is 16%. Among women the corresponding statistics are 48%, 12%, and 9%, respectively.[12]

Conditioning on labor force participation, 70% of women and 64% of men work at the firm. Finally, we observe that both women and men contribute to the pension system at low rates, 31% and 53%, respectively.

2.3.3 Sectors of Employment

To complete the presentation of the data, we highlight important differences across sectors of employment. In Figure 2.1 we show characteristics of the formal, informal, and self-employment sectors: firm size, place of work, pension contributions, cognitive requirements, weekly hours and hourly wages. With the exception of pension contributions, all figures are generated based on data for women only.

The first panel shows the firm size distribution by sector. Around 60% of women working in the formal sector are employed in firms with more than 20 employees. In the informal sector this share falls to approximately 20%, and the typical firm has less than 10 employees. Self-employment is entirely characterized by small firms, where more than 70% of self-employed women work in a one-person venture. The second panel displays the proportion of women by workplace. The majority of women in the formal sector work at the firm, while only 40% of informal workers and less than 20% of the self-employed do so.

In the third panel we show that around 20% of individuals in the informal sector

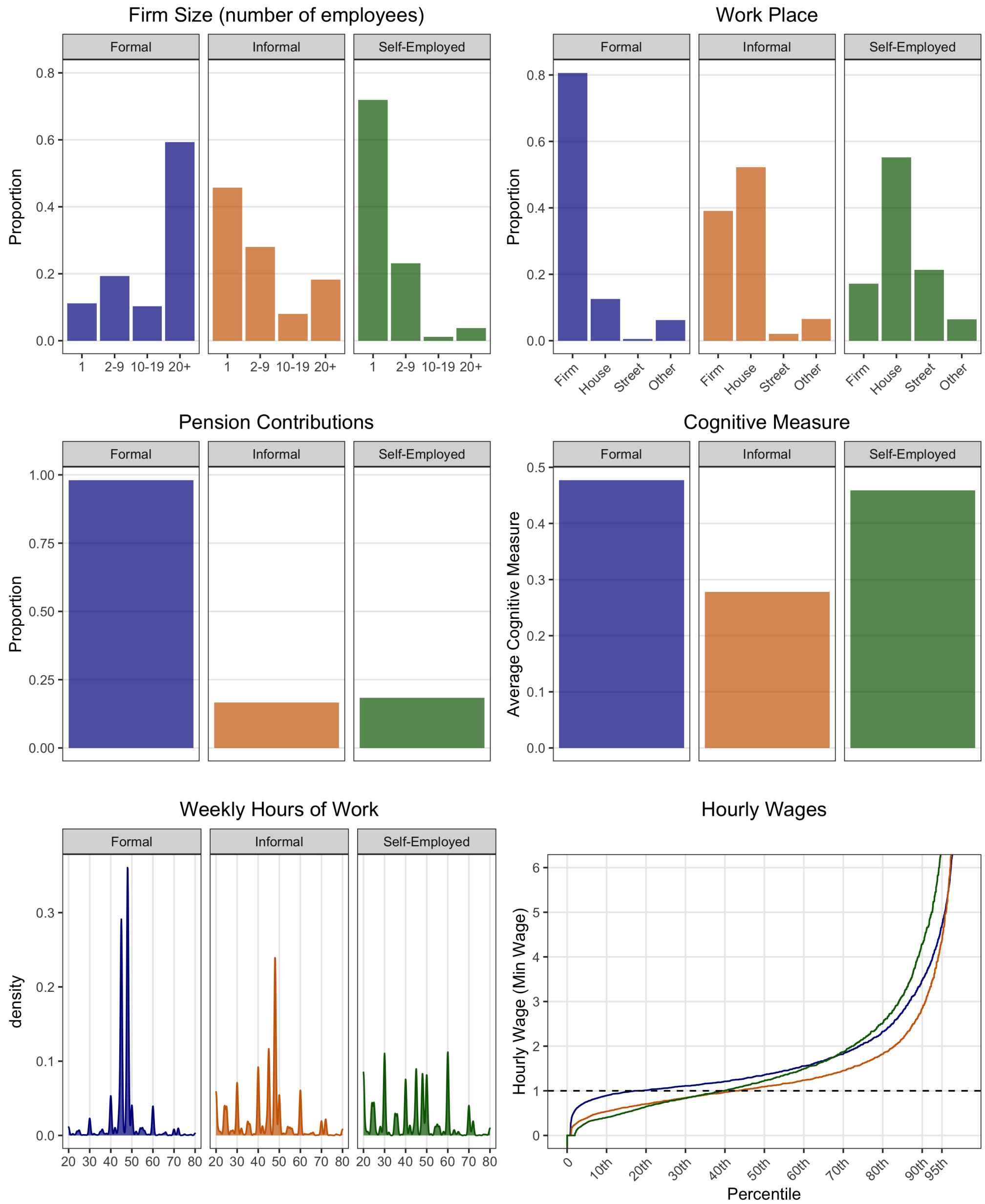
[12]In Table 2.2, there is an ommited sector 'other', such that when we sum this category and the share of individuals unemployed, in the formal, informal and self-employment sectors, we obtain the share of individuals who are participating in the labor force.

Table 2.2: Labor Market Information

Statistic	N	Mean	St. Dev.
Panel A — Women			
Pension contribution indicator	1,993,227	0.316	0.465
Working hours	728,189	44.984	10.094
Log monthly wage	356,597	2.386	0.633
Labor force participation	1,575,946	0.570	0.495
Unemployed	1,575,946	0.080	0.271
Formal sector	1,575,946	0.277	0.448
Informal sector	1,575,946	0.067	0.249
Self-employed	1,575,946	0.050	0.218
Public sector	1,575,946	0.079	0.270
Working at the firm facility	637,059	0.699	0.459
Cognitive measure	204,857	0.479	0.228
Panel B — Men			
Pension contribution indicator	1,943,062	0.530	0.499
Working hours	1,249,947	48.437	8.730
Log monthly wage	533,201	2.609	0.596
Labor force participation	1,563,162	0.888	0.315
Unemployed	1,563,162	0.046	0.209
Formal sector	1,563,162	0.524	0.499
Informal sector	1,563,162	0.080	0.271
Self-employed	1,563,162	0.146	0.353
Public sector	1,563,162	0.053	0.224
Working at the firm facility	1,139,399	0.636	0.481
Cognitive measure	294,468	0.497	0.162

Note: Data from EPS and O*NET. Cohorts born between 1945 and 1995. For the labor market outcomes observations are restricted to individuals between 16 and 59 years old and for years between 1981 and 2016.

Figure 2.1: Characteristics of Sectors of Employment



Note: Data from EPS 2002-2015. All individuals born between 1945 and 1995, ages between 16 and 59. With the exception of the third panel, all graphs restrict to the sample of women only. The first panel shows the proportion of women by firm size and the second panel by workplace across sectors of employment. The third panel displays the proportion of individuals contributing to the pension system. The fourth panel shows the average cognitive requirements, the fifth panel the distribution of weekly hours and the sixth panel the flipped CDF for hourly wage in terms of the minimum wage, in all cases across sectors of employment.

and in self-employment contribute to the pension system. In panel four, we summarize the mean cognitive requirements of occupations associated with each employment scenario and find that the demand for cognitive requirements is highest in the formal sector. In terms of working hours, the formal sector has typical contracts of 45 or 48 hours, and other working arrangements are much less common. For the informal and self-employment sectors there is higher dispersion, especially for self-employment. The last panel shows the wage distributions (cumulative density functions) across sectors. Around 40% of self-employed and informally employed women are earning less than the minimum wage.[13] The formal sector cumulative distribution function stochastically dominates the other two, except at the top wages. The findings from Figure 2.1 let us conclude that informality and self-employment are associated with lower levels of social security contributions and higher levels of labor market risk compared to the formal sector.

2.3.4 Pension System Reform in 2008

In the final part of our analysis we refer to a reform of the pension system that took place in Chile in 2008. This reform aimed to reduce poverty at older ages and the number of individuals with low pensions at retirement. The new pension ends the requirement of a minimum of 20 years of contribution for eligibility to a minimum pension level, and increases the generosity of pensions through a raise in the minimal pension level and through the introduction of a bonus with an implicit tax rate of 30%.

Other changes of the reform affect women in particular: 1) the government covers a woman's pension contribution for each child born alive with an amount that represents 10% of 18 minimum wages, and 2) at the moment of divorce, a judge can determine that a spouse keeps up to 50% of the other spouse's pension funds. The

[13]The minimum wage increased in Chile from 100 US dollars at its introduction in the 70s to almost 400 US dollars in recent years.

goal of these changes is to reduce the gender gap in pensions received at the time of retirement. It is not clear, however, which could be the effect of this reform on women's incentives to work and to remain in the formal sector. On the one hand, the coverage of pension contributions by the government increases the pension savings, so the household needs to work less in the formal sector to obtain the same pension amount. At the same time, married women who do not work have an increase in insurance in the case of divorce, potentially receiving up to half of the husband's pension funds. This also motivates a decrease in labor supply. On the other hand, given that women have pension coverage for one and a half years for each child born, they may have incentives to remain attached to the formal sector and reap a higher contribution at an older age.

2.4 Empirical Strategy

Our empirical strategy follows an event study approach similar to Kuziemko, Pan, Shen, and Washington (2018) and Kleven, Landais, and Søgaard (2019b), exploring time of birth of the first child. The basic model is given by:

$$Y_{imt} = \sum_{\tau=-5}^{8} \beta_\tau 1\{EV_{imt} = \tau\} + \sum_{a=16}^{59} \gamma_a 1\{\text{age}_{imt} = a\} + \nu_i + \varepsilon_{imt}, \tag{2.1}$$

where i indexes individuals, m calendar-month, and t indexes the calendar year. Individuals have their first child at calendar year e_i, so we construct the event time as the distance, in years, relative to the birth of the first child, given by:

$$EV_{imt} = \begin{cases} -5, & \text{if } t - e_i < -5 \\ t - e_i, & \text{if } -5 \leq t - e_i \leq 8 \\ 8, & \text{if } t - e_i > 8 \end{cases}, \tag{2.2}$$

We cap the extreme points, 5 years before and 8 yeas after the first birth, as in Kuziemko, Pan, Shen, and Washington (2018). In our specification we include as controls age and individual fixed effects. We estimate the regressions separately for men and women, using always event year -2 as the comparison level, which is omitted from Equation 2.1. The choice of the annual level stems from data constrains — for a high fraction of women in our sample we can only identify the year of first birth, but not the exact month.[14]

Recent research by Goodman-Bacon (2018), Callaway and Sant'Anna (2020) and Sun and Abraham (2020) discusses the issues with non-convex weighting when using two-way fixed effect estimators in event studies, where there is variation in treatment timing across units and dynamic treatment effects. We follow Sun and Abraham (2020) and estimate the parameters of interest, β_τ, without the contamination effects from other periods. As we show in our results section, our estimates point in the direction of dynamic treatment effects for several outcomes, which may pose challenges for papers using two-way fixed effects in the context of childbirth event studies. The estimator, however, constraints the treatment effect to be homogeneous across different cohorts, a hypothesis that it is strong in our setting.[15]

We restrict our sample to individuals that have at least one child — therefore, we do not explore selection into becoming a parent. Our identification hypothesis is that the *pre-birth* outcomes are exogenous to the birth of the first child. Our approach allows for some anticipatory behavior, requiring only that for a non empty set of *pre-birth* years this anticipatory behavior is non-existent. We do confirm this intuition showing that pre-birth estimates are centered around zero for both men and women.

[14]Additionally, the computational burden of the estimator of Sun and Abraham (2020) is substantially higher with the monthly specification.

[15]We define a "cohort" as a group of women that have their first birth in a particular age.

The outcome variable varies in each exercise, including indicator variables for labor force participation, employment in specific sectors (formal, informal and self-employment) and place of work, among others. The coefficient β_τ captures the difference of average Y_{it}, τ years apart from the birth of the first child in comparison with two years before the event, conditional on age, and individual fixed effects. Our identification strategy explores, therefore, individual level variation in the timing of births — estimating within-individual evolution of outcomes. In most of our graphs we show the coefficient of interest β_τ from Equation 2.1 as a percentage of the counterfactual outcome, when we exclude the contribution of the event dummies as in Kleven, Landais, and Søgaard (2019b).

2.5 Results

2.5.1 Labor Supply, Wages and Occupations

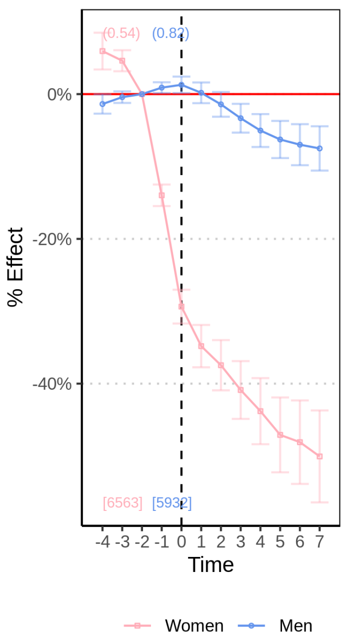
We begin our analysis by showing the evolution of labor supply choices and wages before and after the event of the birth of the first child. Figure 2.2 shows the event study coefficients from Equation 2.1 as a percentage of the counterfactual outcome. Two years before the birth of the first child ($\tau = -2$), 54% of women and 82% of men are working. The labor force participation (LFP) rates of men and women diverge further two years after the birth: there is a reduction in labor force participation of approximately 40% for women, but there are no effects for men with respect to $\tau = -2$. This initial decline experienced by women is persistent over time. We also report results for low and highly educated individuals, and observe that low educated women are more likely to leave the labor force than highly educated women (a year after the first birth, there is an approximate decrease of over 40% and around

20% with respect to $\tau = -2$, respectively). Our estimates mirror the results from the existing literature, being close to US and UK estimates, but larger than the ones from Scandinavian countries (Kuziemko, Pan, Shen, and Washington (2018), Kleven, Landais, Posch, Steinhauer, and Zweimüller (2019a), Kleven, Landais, and Søgaard (2019b), Berniell, Berniell, De la Mata, Edo, and Marchionni (2021)).[16] In addition, we show heterogeneity by marital status, previously unexplored in related event studies. We find that married women experience an approximate decline of 40% in LFP and single women around 25% a year after the birth, relative to $\tau = -2$. The difference by marital status may arise due to social norms, insurance, or due to the fact that the income of the partner contributes to joint family resources in such a way that employment in the presence of a child and a husband becomes less desirable.

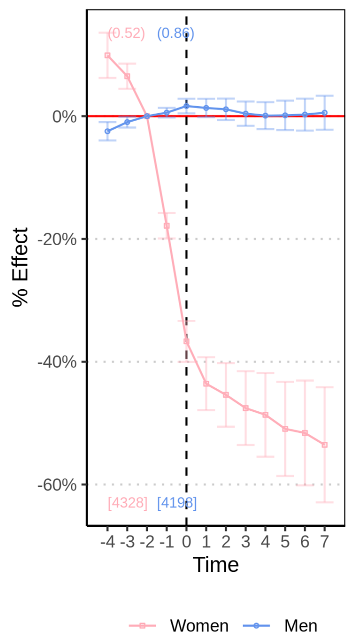
Regarding hourly wages, Figure 2.3 shows there is an initial 5% fall for women a year after the birth, with respect to $\tau = -2$, but this drop becomes more pronounced over time representing a 20% fall by the sixth year. There are heterogeneous results by education level, where we observe a fall in hourly wages for highly educated women but not for low educated women in Panels (b) and (c). The fall in wages for women with high education may be driven by slower rates of human capital accumulation, or different commitment to the job in the presence of children. It could further be driven by the fact that these women switch to lower paying and less demanding jobs. The stable wage level of low educated women, on the other hand, could be due to selection: those who remain at work are the most productive, preventing a decrease in hourly wages.

[16] We find that our estimates are larger than in Berniell, Berniell, De la Mata, Edo, and Marchionni (2021) that find a decrease in LFP of 15% after childbirth. This may be due to different sample selection and empirical strategy.

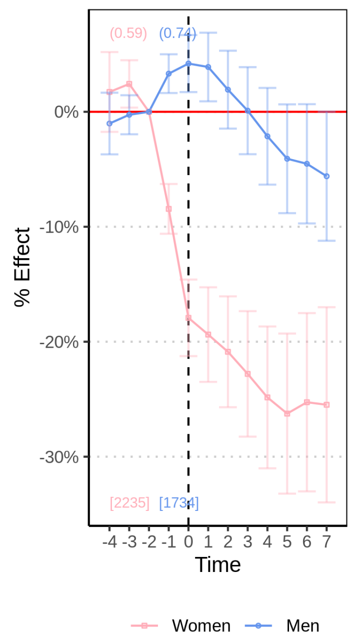
Figure 2.2: Labor Supply



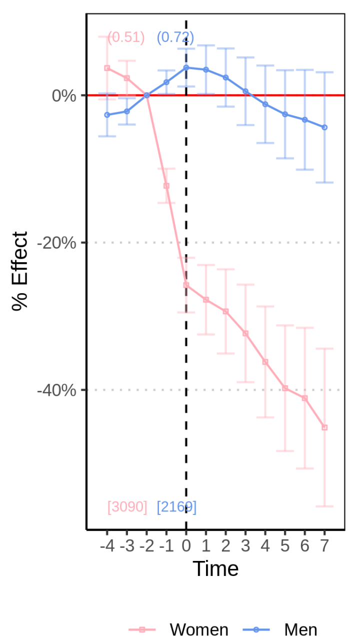
(a) LFP: All



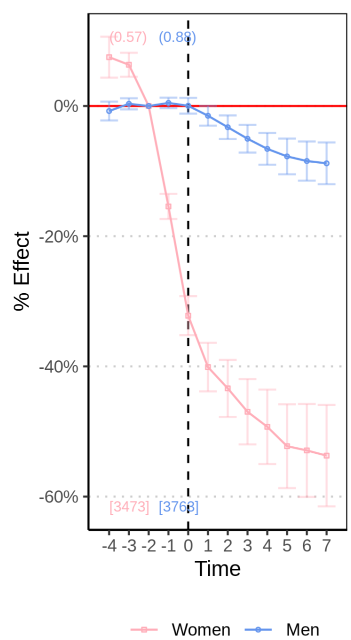
(b) LFP: LE



(c) LFP: HE



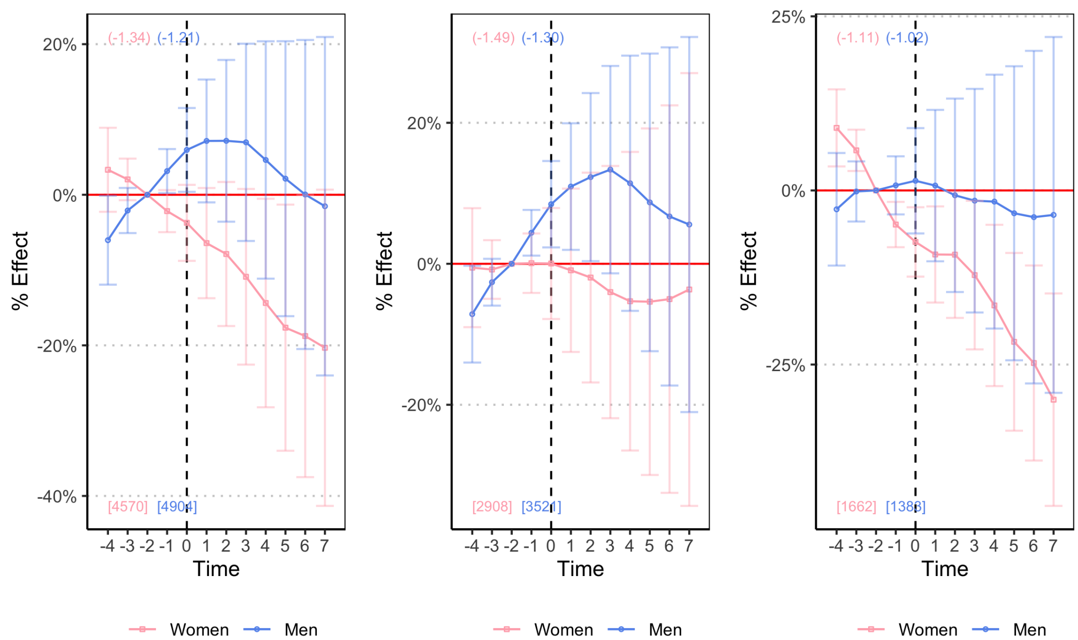
(d) LFP: Single



(e) LFP: Married

Note: Each graph plots the β_τ coefficients from Equation 2.1 as a percentage of the counterfactual outcome, together with 95% confidence intervals. The baseline coefficient is set at period -2. Numbers in parenthesis display the outcome variable level in the reference period and numbers in brackets the number of individuals in each analysis. LE stands for Low Educated and HE for highly educated. The outcome variable is a binary variable which equals 1 when the individual is in the labor force. Panel (a) uses the full samples, while panels (b)-(e) use sub-samples, respectively: low educated (high school or less), highly educated (some college or more), single and married.

Figure 2.3: Hourly Wages



(a) Wages: All

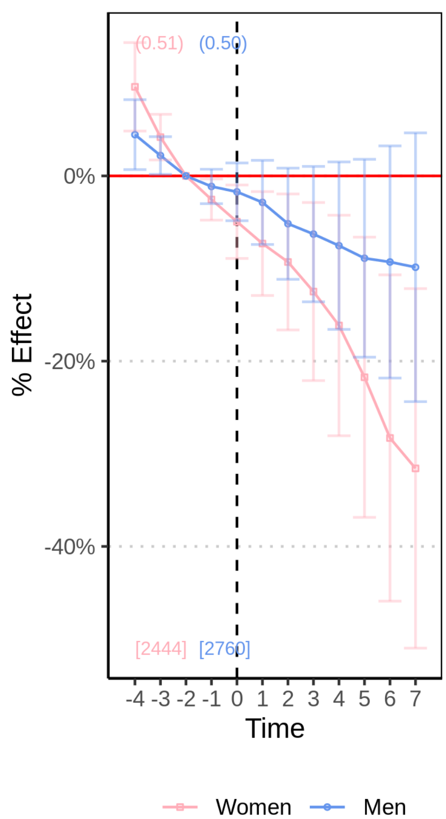
(b) Wages: LE

(c) Wages: HE

Note: Each graph plots the β_τ coefficients from Equation 2.1 together with the 95% confidence intervals. The baseline coefficient is set at period -2. Numbers in parenthesis display the outcome variable level in the reference period and numbers in brackets the number of individuals in each analysis. LE stands for Low Educated and HE for highly educated. The outcome variable is the hourly wages. Panel (a) uses the full samples, while panels (b)-(c) for sub-samples, respectively: low educated (high school or less) and highly educated (some college or more). Results by marital status are available upon request.

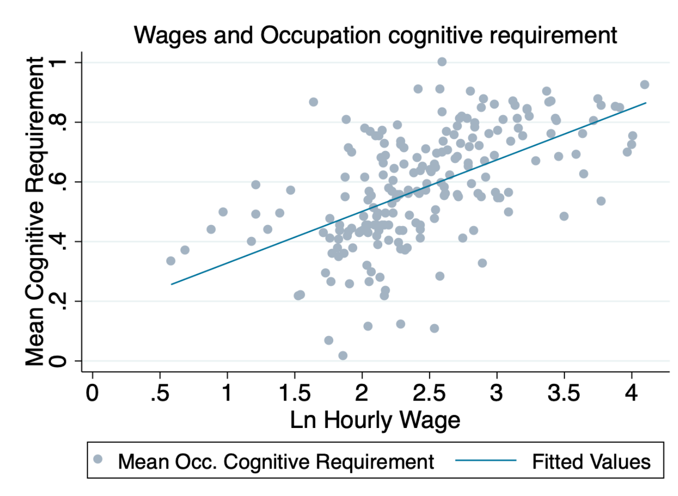
To better understand the reason for the fall in wages after childbirth we perform an event study where we analyze if women move towards occupations that have lower wages. We proceed in two steps. First, we show that women move towards occupations with lower cognitive content. Second, we report a positive correlation between wages and cognitive content at the occupational level. In the first step, we classify occupations by their cognitive task requirements, where we consider core math, analytical and verbal skills. We sort the occupations on a unit interval [0,1], where 1 represents the occupation with the highest cognitive content. Figure 2.4 shows that there is about a 10% decrease in cognitive tasks performed at the job a year after the event of motherhood and a decrease of almost 30% by the sixth year, with respect to $\tau = -2$. In the second step, we compute the mean wages at the occupational level. With information on cognitive skill requirements for 207 occupations, we graph the relation between wages and cognitive skill requirements in Figure 2.5, where we report a positive relation. This suggests that as women move towards less cognitive occupations after birth, they are more likely to move towards jobs with lower wages.

Figure 2.4: Occupation Cognitive Requirements



Note: The graph plots the β_τ coefficients from Equation 2.1 as a percentage of the counterfactual outcome, together with 95% confidence intervals. The baseline coefficient is set at period -2. Numbers in parenthesis display the outcome variable level in the reference period and numbers in brackets the number of individuals in each analysis. The outcome variable is the average cognitive measure of the occupation.

Figure 2.5: Correlation Wages and Cognitive Skill Requirements at Occupational level



Note: Data from EPS and O*NET. The sample includes 207 occupations. The cognitive skill requirement is obtained performing principal component analysis on 18 descriptors of cognitive task requirements. We keep the first principal component and normalize the measure on the interval [0,1].

2.5.2 Sector of Employment

We also study the effects of parenthood on sector of employment, distinguishing between three sectors: formal, informal and self-employment. These sectors differ in the degree of flexibility, as depicted in Figure 2.1. The formal sector is the most rigid, where the majority of employees typically work 48 hours and the usual place of work is the firm. The informal sector is more flexible than the formal sector in the hours dimension, but still very inflexible on the workplace dimension as around 40% of the employees work at the firm. Self-employment offers the most flexible work arrangements, as is evident from the histogram of hours worked - which is very smooth over the range of working hours - and from the fact that over 50% of individuals who are self-employed work from home.

We start the analysis with formal employment. We observe in panel (a) of Figure 2.6 that, conditional on working, women decrease employment in the formal sector after the birth of the first child. A year after the birth, there is a 13% decrease in formal employment for women, with respect to $\tau = -2$. In contrast, men increase their participation in formal employment by 3% in the first year after birth. Figure 2.14 reports the results unconditional on working, where we observe a decrease in employment for women in the formal sector of 50% a year after the first birth with respect to $\tau = -2$. This strong decline in formal employment may be driving the fall in labor force participation. We report heterogeneous results by education level on panels (b) and (c) of Figure 2.6. Low educated women decrease formal work by 17% and highly educated women by 8%. Figure 2.14 in Section 2.7 shows that the fall in formal employment (unconditional on working) for low educated women is above 70% while for highly educated women above 30% in the years after childbirth. This large difference may explain the larger fall in labor force participation of low educated women shown in Figure 2.2. Panels (d) and (e) show that the formal employment response of single and married women is very similar.

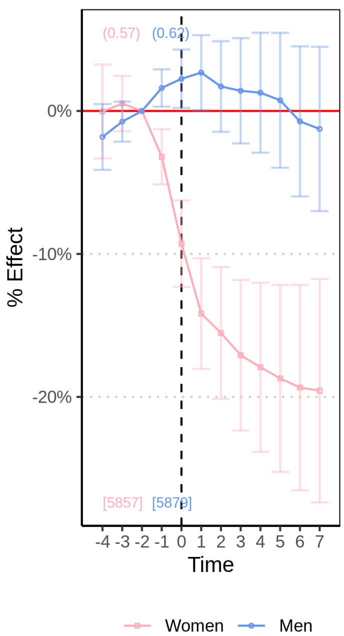
We now turn to the results on informal work. Our study distinguishes formal from informal work by the existence of a formal contract of employment. We understand that a labor contract for a determined time period, establishing rights and obligations of the worker, determines a working formal relation. This contract protects the worker from unexpected events such as unemployment, and provides with benefits such as social security and labor union participation (Díaz and Gálvez, 2015). We observe that for those individuals who are working under a formal contract in our sample, 98% of them are contributing to the pension system. For informal workers, we find that only 23% are contributing to the pension system.[17] Therefore, workers can be under an informal contract in the private sector and still contribute to the pension system. We observe in panel (a) of Figure 2.7 that there are no significant changes in informal work for men and women after the birth of the first child. There

[17]Own calculations based on self-reported pension contributions from EPS data.

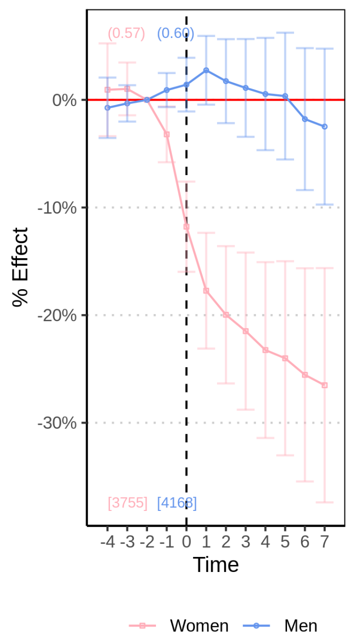
are also no significant changes for low and highly educated women (panels (b) and (c)) nor for single or married women (panels (d) and (e)). If we analyze the results unconditional on employment, we observe in panels (b) and (c) of Figure 2.15 in Section 2.7 that there is a fall of 40% in informal employment a year after the birth of the first child for both low and highly educated women. However, low educated women experience a persistent effect that lasts many years after the birth. This fall is consistent with a larger fall in labor force participation among low educated women that is persistent after childbirth. Our results on informal employment differ from Berniell, Berniell, De la Mata, Edo, and Marchionni (2021) because we consider a different definition of informality, as described on Section 2.2, and employ different samples and methodology.

Finally, we report results on self-employment conditional on employment in Figure 2.8. In panel (a) we observe that there is an increase of above 60%, with respect to $\tau = -2$, on the probability of being self-employed for women while there are no effects for men. This effect is persistent and increasing, reaching a 100% by the 6th year after the birth of the first child. We also show results by education level on panels (b) and (c). A year after the birth, low educated women increase self-employment by around 60% while highly educated women by a 100%. Appendix Figure 2.16 shows that, unconditional on employment, the increase in self-employment after childbirth is driven almost entirely by highly educated women.

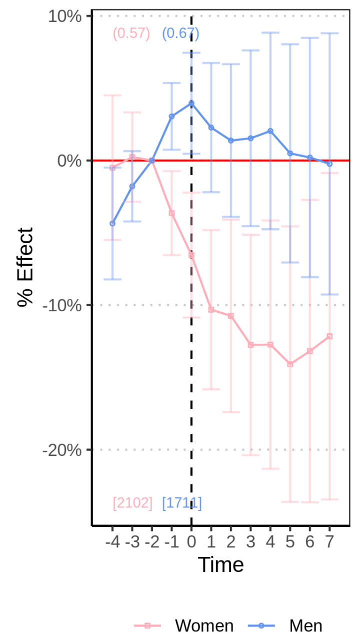
Figure 2.6: Formal Employment - Conditional on Working



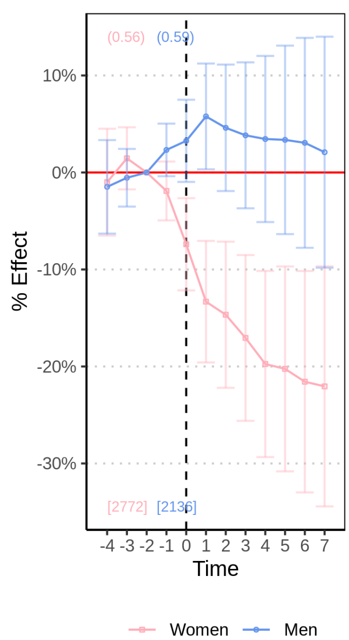
(a) Formal: All



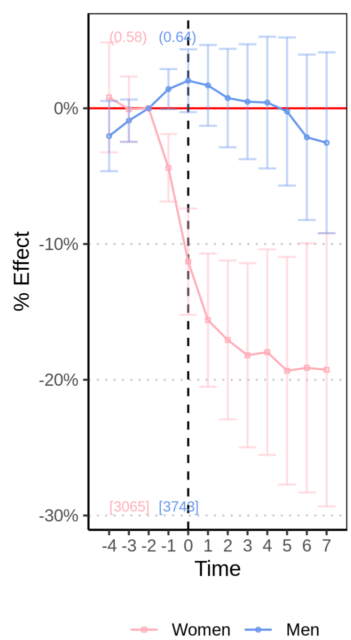
(b) Formal: LE



(c) Formal: HE



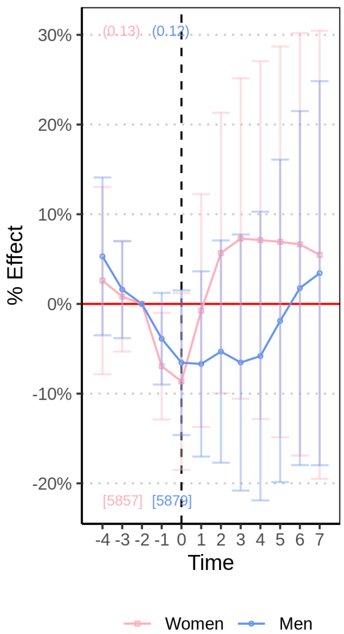
(d) Formal: Single



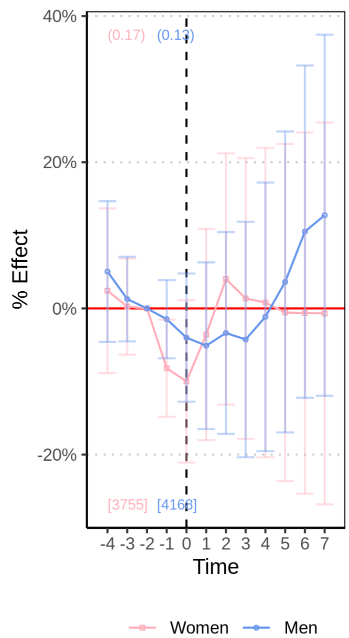
(e) Formal: Married

Note: Each graph plots the β_τ coefficients from Equation 2.1 as a percentage of the counterfactual outcome, together with 95% confidence intervals. The baseline coefficient is set at period -2. Numbers in parenthesis display the outcome variable level in the reference period and numbers in brackets the number of individuals in each analysis. LE stands for Low Educated and HE for highly educated. The outcome variable is a dummy variable for formal employment. Panel (a) uses the full samples, while panels (b)-(e) for sub-samples, respectively: low educated (high school or less), highly educated (some college or more), single and married.

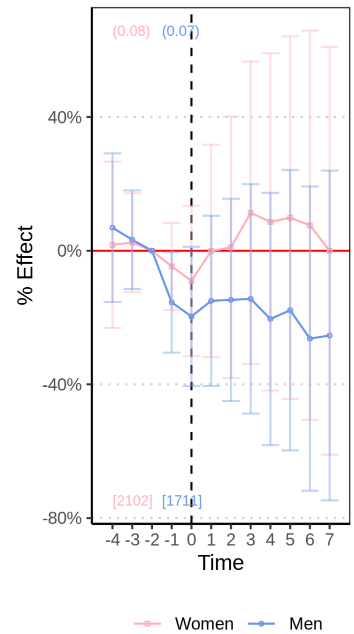
Figure 2.7: Informal Employment - Conditional on Working



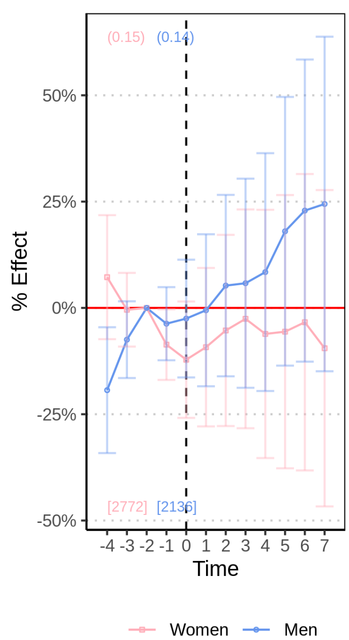
(a) Informal: All



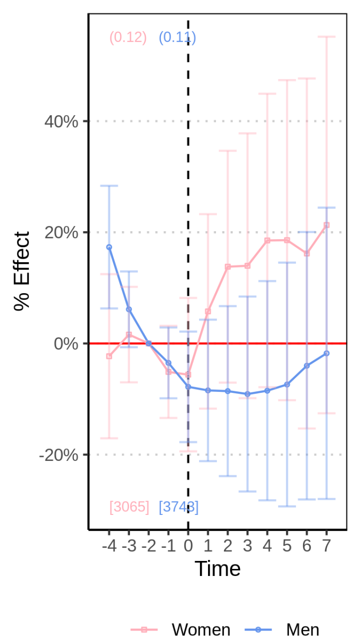
(b) Informal: LE



(c) Informal: HE



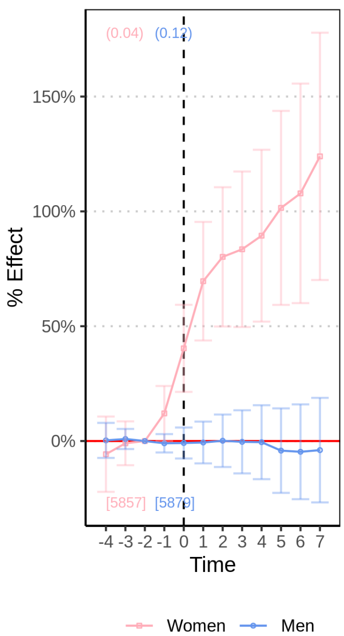
(d) Informal: Single



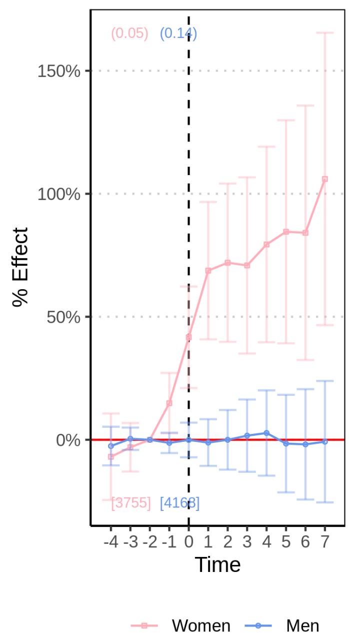
(e) Informal: Married

Note: Each graph plots the β_τ coefficients from Equation 2.1 as a percentage of the counterfactual outcome, together with 95% confidence intervals. The baseline coefficient is set at period -2. Numbers in parenthesis display the outcome variable level in the reference period and numbers in brackets the number of individuals in each analysis. LE stands for Low Educated and HE for highly educated. The outcome variable is a dummy variable for informal employment. Panel (a) uses the full samples, while panels (b)-(e) for sub-samples, respectively: low educated (high school or less), highly educated (some college or more), single and married.

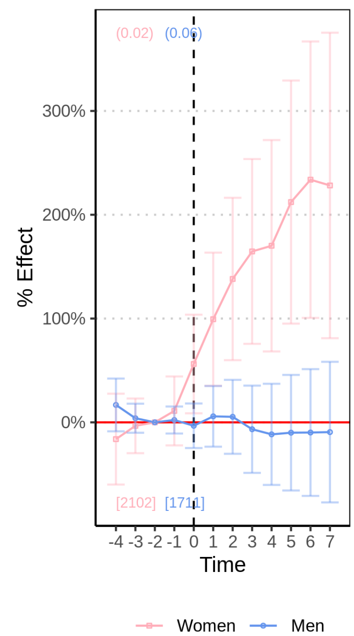
Figure 2.8: Self-Employment - Conditional on Working



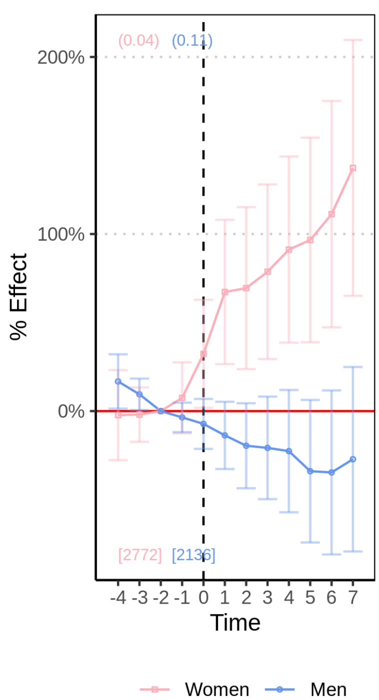
(a) Self-Employment: All



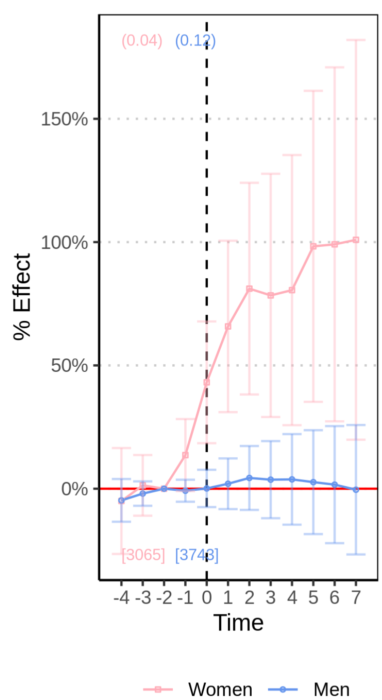
(b) Self-Employment: LE



(c) Self-Employment: HE



(d) Self-Employment: Single



(e) Self-Employment: Married

Note: Each graph plots the β_τ coefficients from Equation 2.1 as a percentage of the counterfactual outcome, together with 95% confidence intervals. The baseline coefficient is set at period -2. Numbers in parenthesis display the outcome variable level in the reference period and numbers in brackets the number of individuals in each analysis. LE stands for Low Educated and HE for Highly Educated. The outcome variable is a dummy variable for self-employment. Panel (a) uses the full samples, while panels (b)-(e) for sub-samples, respectively: low educated (high school or less), highly educated (some college or more), single and married.

2.5.3 Flexible work arrangements

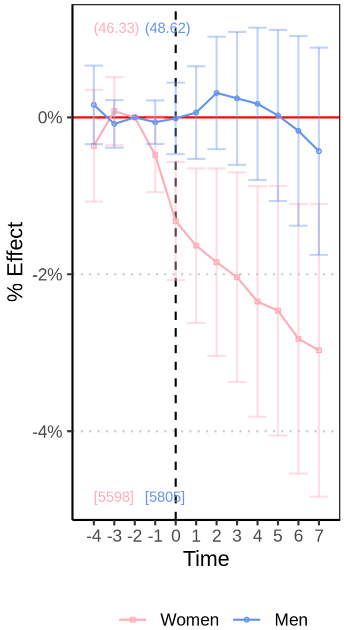
The results from the previous section are very consistent with the fact that women may try to find work arrangements that are flexible after childbirth. We observe that the decrease in formal work, the lack of significant changes in informal work and the increase in self-employment, all conditional on employment, are aligned with the degree of flexibility of these sectors, where formal and self-employment are at the opposite ends of the spectrum. We now provide results on how parents choose hours and place of work after the event of childbirth. While the results on hours of work (panels (a)-(c) of Figure 2.9) are consistent with findings in related literature (Kleven, Landais, and Søgaard (2019b), Berniell, Berniell, De la Mata, Edo, and Marchionni (2021)), we bring new insights into a different dimension of job flexibility: the place of work. Panel (d) shows that after childbirth women are less likely to work at the firm while men experience no effects. We observe heterogeneous effects by education level on the hours and workplace dimensions, as highly educated women are less likely to work at the firm and experience no change in hours of work after childbirth. In contrast, low educated women decrease their hours of work and remain working at the firm. This is potentially related to job flexibility available for low and highly educated women in self-employment. We observe in the data that 54% of low educated women (high school or less) do not work at the firm, but the share increases to 71% for those with more than high school education.[18]

2.5.4 Insurance

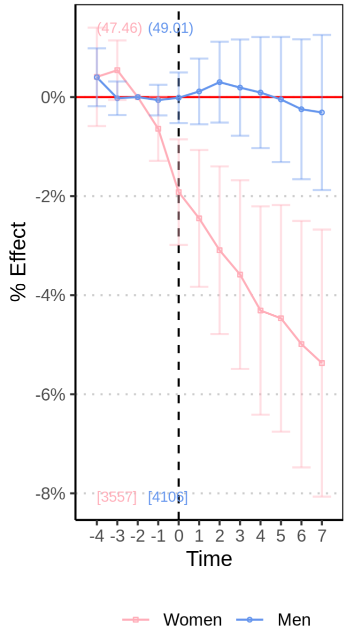
One of the objectives of this paper, apart from studying men and women's labor market behavior, is to study their insurance decisions, which include pension contributions and health coverage. For individuals in the formal sector, contributions

[18]The differences in workplace flexibility in self-employment are also evident for men. The share of low educated men not working at the firm is 58%, while it is 79% for the highly educated.

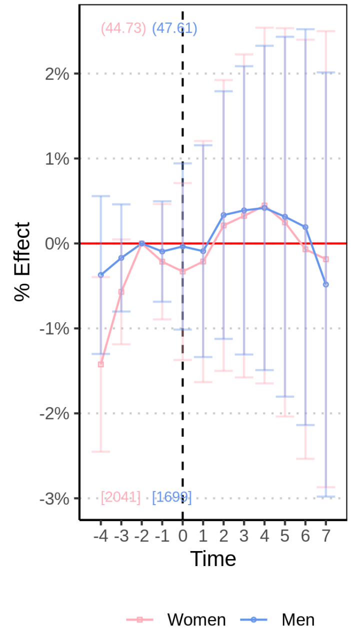
Figure 2.9: Flexible Work Arrangements



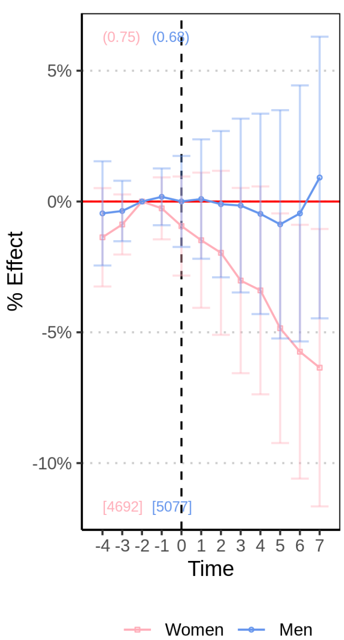
(a) Hours: All



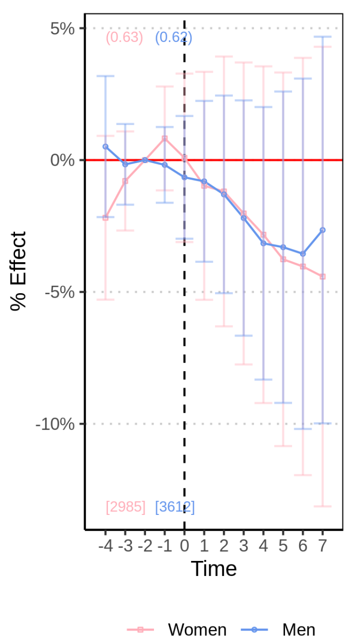
(b) Hours: LE



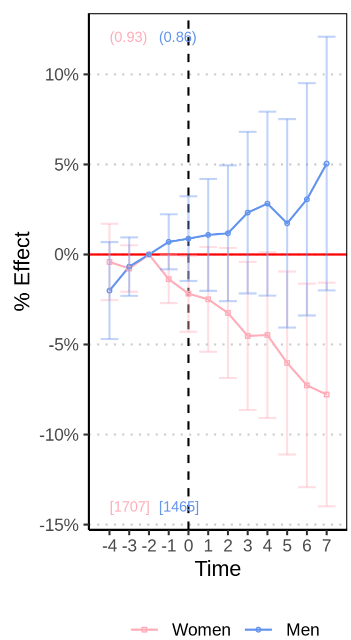
(c) Hours: HE



(d) Workplace: All



(e) Workplace: LE



(f) Workplace: HE

Note: Each graph plots the β_τ coefficients from Equation 2.1 as a percentage of the counterfactual outcome, together with 95% confidence intervals. The baseline coefficient is set at period -2. Numbers in parenthesis display the outcome variable level in the reference period and numbers in brackets the number of individuals in each analysis. LE stands for Low Educated and HE for Highly Educated. The outcome variable for panels (a)-(c) are hours of work and for panels (d)-(f) is a dummy for workplace at the firm site. Panels (a) and (d) use the full sample, panels (b) and (e) the sub-sample of low educated individuals (high school or less), and panels (c) and (f) highly educated individuals (some college or more). Results by marital status are available upon request.

to social security are part of the formal labor contract. However, there may be voluntary contributions from individuals in the informal and self-employment sectors. In our sample, 23% and 22% of informal and self-employed workers, respectively, contribute to the pension system. In Panel (a) of Figure 2.10, we report that there is a decrease in pension contributions above 5% for women in the first year after childbirth, with respect to $\tau = -2$, while there are no significant changes for men. This is a persistent fall for women, reaching over 10% by the sixth year after the first birth. Panels (b) and (c) evidence that the behavior is consistent across education levels.[19] Interestingly, we observe in Panels (d) and (e) that it is married women who, by the second year after childbirth, experience a decrease of almost 10% in pension contributions with respect to $\tau = -2$. In the case of single women, the decrease is of 5% by the same year. Given that married women are more likely to leave the labor force after childbirth, we explore pension contributions unconditional on working. Appendix Figure 2.17 shows that married women decrease their contributions by over 40% and single women by 25% a year after childbirth, with respect to $\tau = -2$. In both cases, pension contributions continuously decrease many years after childbirth. This different behavior by marital status may have implications in the long run in the case of divorce, where married women who did not contribute to the pension system could be adversely affected, especially when married to an individual without pension funds.[20]

In relation to health insurance, before childbirth 93% of women and 90% of men report having health insurance in Chile. Panel (a) in Figure 2.11 reports the effects of childbirth on access to health coverage, where we observe no significant changes for

[19] We also perform this analysis using administrative records of pension contributions instead of self-reported data. We also find that highly educated women decrease their pension contributions conditional on working. Results are available upon request.

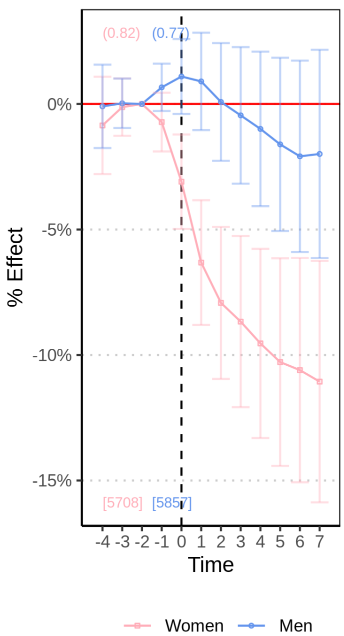
[20] Since 2008, new legislation contemplates the transfer of part of the pension funds to the spouse that was economically affected during marriage (it is ruled by a judge). It should not exceed 50% of the accumulated funds during marriage of the spouse that has to contribute.

neither men and women. In this case, the available data does not allow to follow the same person monthly before and after birth, as the question about health insurance is not retrospective in the surveys. Hence, our event studies rely on cross-sectional data where there is substantial variation in the date of birth of the first child. In addition, we explore the effects of childbirth on the quality of their health insurance, given by whether it is public or private. We find that there is a fall of almost a 100% in the share of women with private health coverage a year after childbirth, while there are no significant effects for men. This may be related to women's lower economic conditions, as they are more likely to leave the labor force and experience lower wages after childbirth.

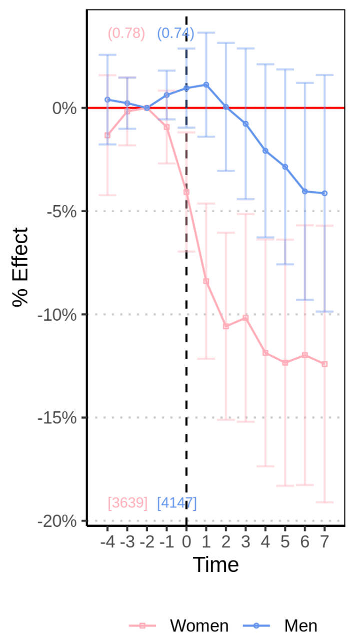
2.5.5 Pension System Reform in 2008

In this section we analyze the effects of the pension system reform in 2008 in formal employment and labor supply decisions. We proceed by evaluating the responses of men and women before and after this reform was implemented. In particular, we perform event studies for those who had children before and after 2008, while keeping individuals from the same cohorts in each analysis. In Panel (a) of Figure 2.12, we report the labor supply responses of individuals who had a child before 2008. In Panel (b), we report the same outcome for individuals who gave birth after 2008. We observe that there are no differences in labor supply responses between those groups. However, Figure 2.13 shows a different picture. We document the responses in formal work, conditional on employment, for individuals that had children before 2008 (Panel (a)) and after 2008 (Panel (b)). We observe that women who had children after the reform are more likely to remain in the formal sector after the birth of the first child, suggesting that the policy encourages formal labor market attachment.

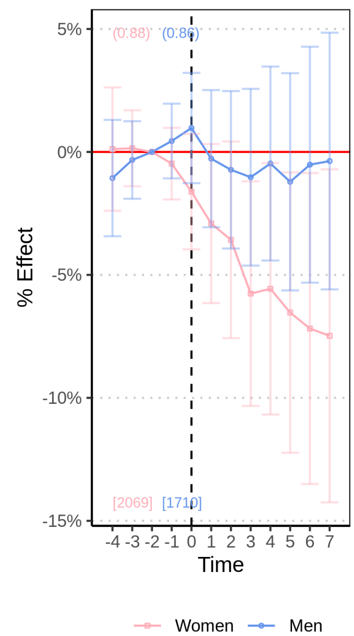
Figure 2.10: Pension Contribution



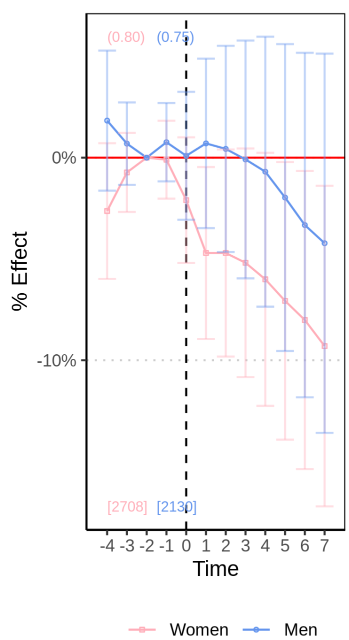
(a) Pension: All



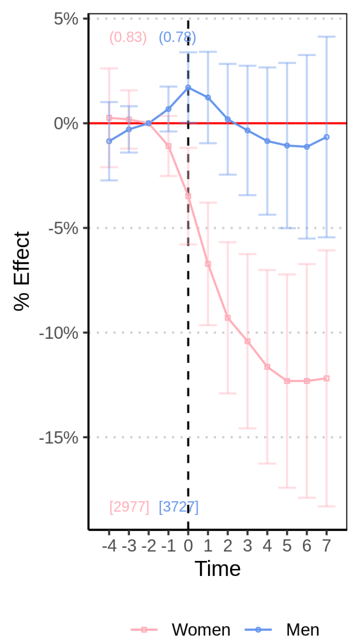
(b) Pension: LE



(c) Pension: HE



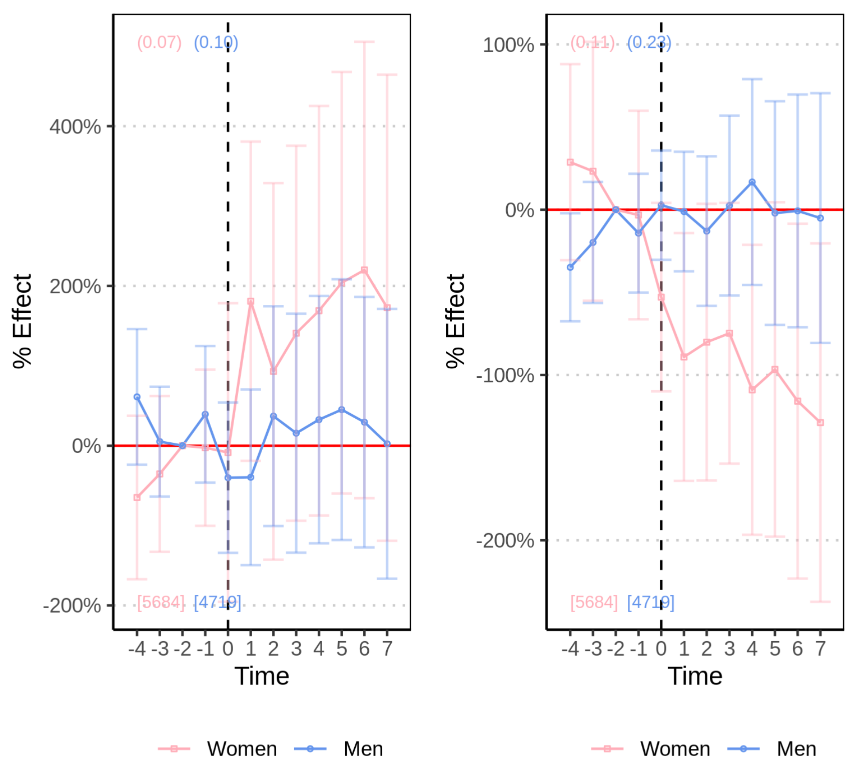
(d) Pension: Single



(e) Pension: Married

Note: Each graph plots the β_τ coefficients from Equation 2.1 as a percentage of the counterfactual outcome, together with 95% confidence intervals. The baseline coefficient is set at period -2. Numbers in parenthesis display the outcome variable level in the reference period and numbers in brackets the number of individuals in each analysis. LE stands for Low Educated and HE for Highly Educated. The outcome variable is a dummy variable for pension contribution (self-reported). Panel (a) uses the full samples, while panels (b)-(e) for sub-samples, respectively: low educated (high school or less), highly educated (some college or more), single and married.

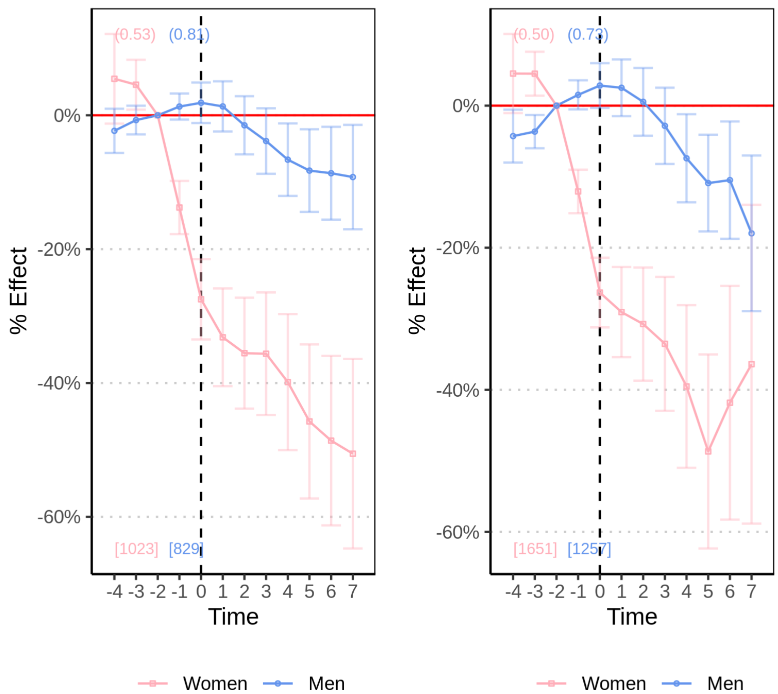
Figure 2.11: Health Insurance



(a) No Health Insurance: All (b) Private Health Insurance: All

Note: Each graph plots the β_τ coefficients from Equation 2.1 as a percentage of the counterfactual outcome, together with 95% confidence intervals. The baseline coefficient is set at period -2. Numbers in parenthesis display the outcome variable level in the reference period and numbers in brackets the number of individuals in each analysis. The outcome variables are dummy variables for no health insurance (panel a) and private health insurance (panel b).

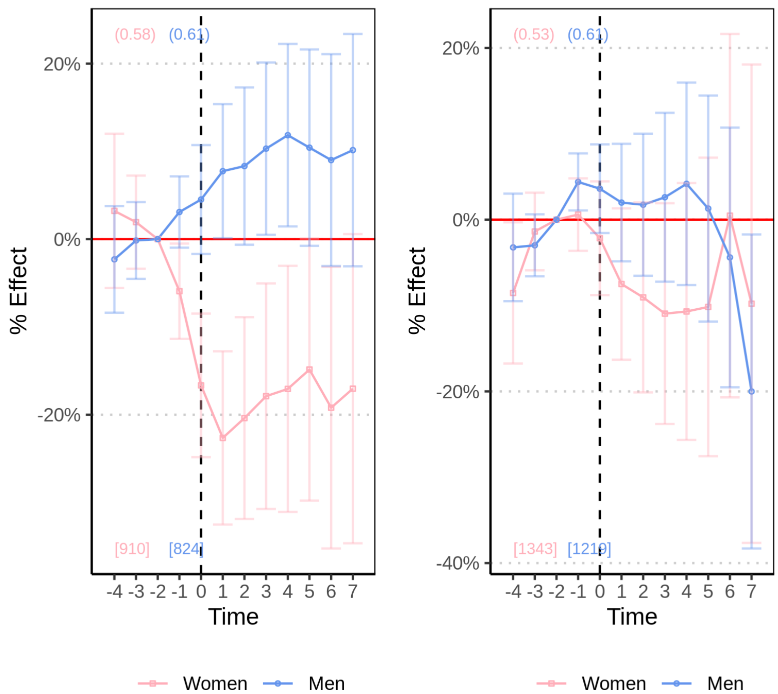
Figure 2.12: Labor Supply - Pension Reform 2008



(a) Year of Birth Before 2008 (b) Year of Birth After 2008

Note: Each graph plots the β_τ coefficients from Equation 2.1 as a percentage of the counterfactual outcome, together with 95% confidence intervals. The baseline coefficient is set at period -2. Numbers in parenthesis display the outcome variable level in the reference period and numbers in brackets the number of individuals in each analysis. The outcome variable is a dummy variable for labor force participation. Panel (a) estimates for the sub-sample of individuals who gave birth to children before 2008 and panel (b) after 2008.

Figure 2.13: Formal Employment Conditional on Working - Pension Reform 2008



(a) Year of Birth Before 2008 (b) Year of Birth After 2008

Note: Each graph plots the β_τ coefficients from Equation 2.1 as a percentage of the counterfactual outcome, together with 95% confidence intervals. The baseline coefficient is set at period -2. Numbers in parenthesis display the outcome variable level in the reference period and numbers in brackets the number of individuals in each analysis. The outcome variable is a dummy variable for formal employment, conditional on working. Panel (a) estimates for the sub-sample of individuals who gave birth to children before 2008 and panel (b) after 2008.

2.6 Conclusion

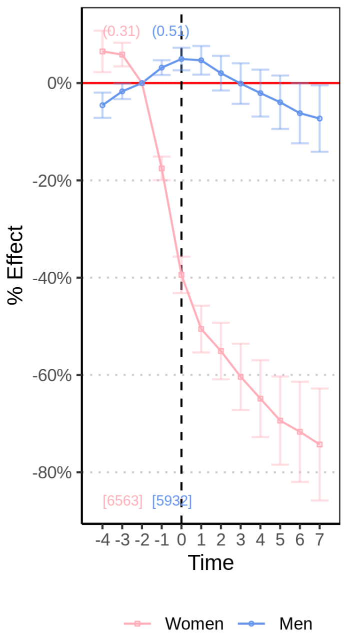
In this paper we analyze the labor market and insurance decisions of men and women around the time of childbirth in Chile. This is a market with three distinct sectors: formal, informal and self-employment. A formal worker has a clear labor contract that protects against unexpected events such as unemployment, and ensures benefits such as social security and labor union participation rights. An informal worker does not have such contract and a self-employed individual works independently. These sectors also differ in hours and place of work, firm size, cognitive tasks, among other characteristics.

Using an event studies approach, we find that the fall in women's wages after childbirth is associated with their switch into less cognitive occupations, which have lower wages. In addition, we observe that there is a decrease in formal work, no significant changes in informal work and an increase in self-employment for women after childbirth. These results are aligned with the degree of flexibility of these sectors, where formal and self-employment are at opposite ends of the spectrum. Moreover, women with high education are more likely to work remotely after childbirth, while low educated women experience no changes on work location. Regarding insurance choices, we observe a fall in female pension contributions, which is larger for married women, and a fall in female private health insurance after childbirth, while men experience no effects. In a final exercise, we explore the effects of the 2008 pension system reform in Chile, which aimed to decrease the gender gap in pensions. We observe that women who had children after the reform are less likely to leave formal employment, in comparison to women who had children before 2008.

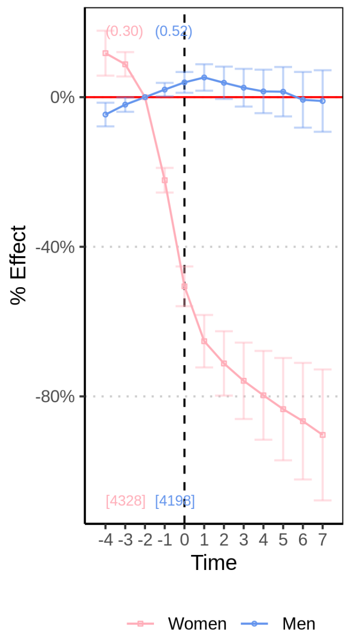
We expect that our work informs policy makers on the costs associated with labor market behavior and insurance decisions after childbirth in a country with widespread informality. Gender gaps, not only in wages and labor market attachment, but also in occupational sorting, sectors of employment and insurance, may have long-run welfare implications. Further work should study the effects of policies that aim to reduce such gaps in the context of developing countries, taking into account the role of children as a major driver for differential gender behavior.

2.7 Appendix

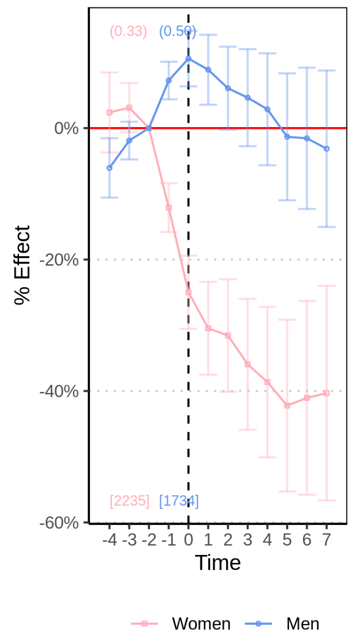
Figure 2.14: Formal Employment - Unconditional on Working



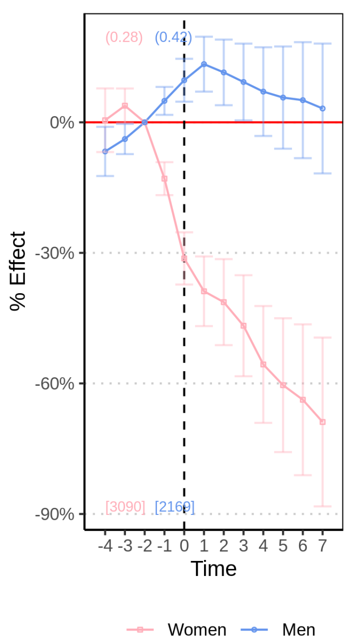
(a) Formal: All



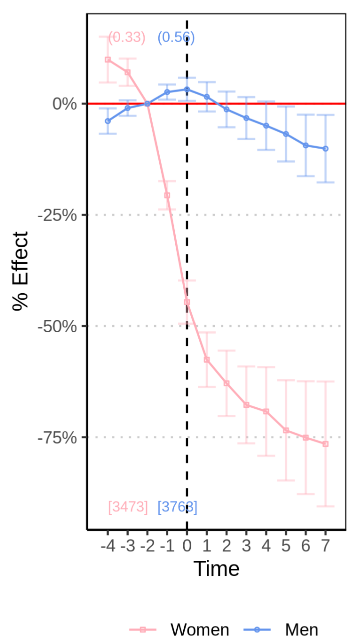
(b) Formal: LE



(c) Formal: HE



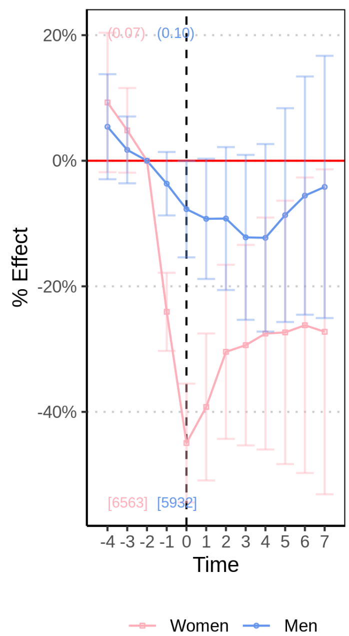
(d) Formal: Single



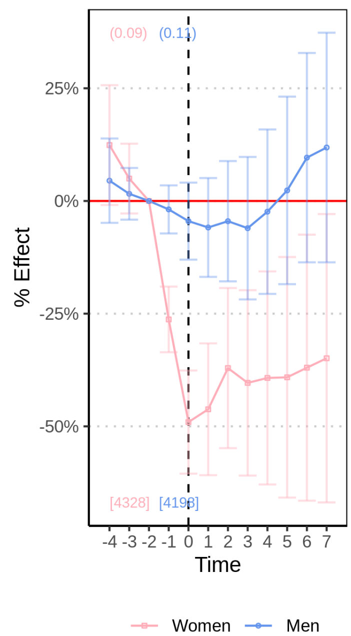
(e) Formal: Married

Note: Each graph plots the β_τ coefficients from Equation 2.1 as a percentage of the counterfactual outcome, together with 95% confidence intervals. The baseline coefficient is set at period -2. Numbers in parenthesis display the outcome variable level in the reference period and numbers in brackets the number of individuals in each analysis. LE stands for Low Educated and HE for highly educated. The outcome variable is a dummy variable for formal employment. Panel (a) uses the full samples, while panels (b)-(e) for sub-samples, respectively: low educated (high school or less), highly educated (some college or more), single and married.

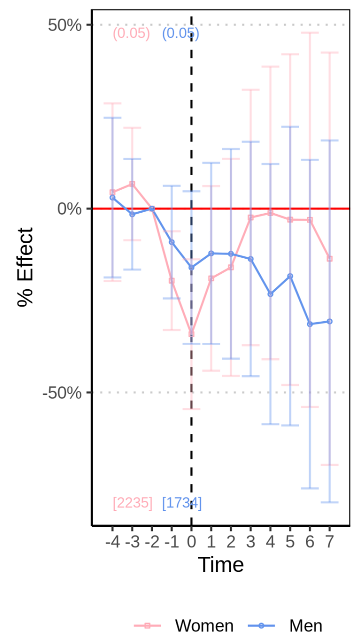
Figure 2.15: Informal Employment - Unconditional on Working



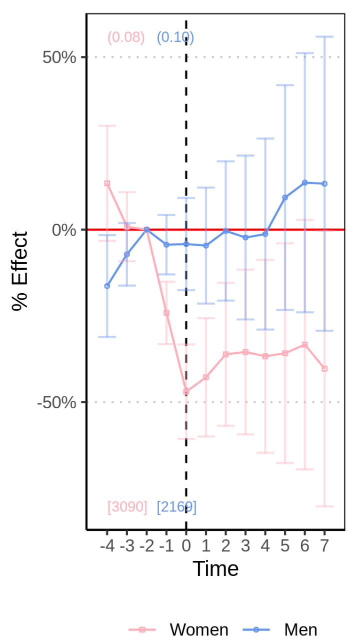
(a) Informal: All



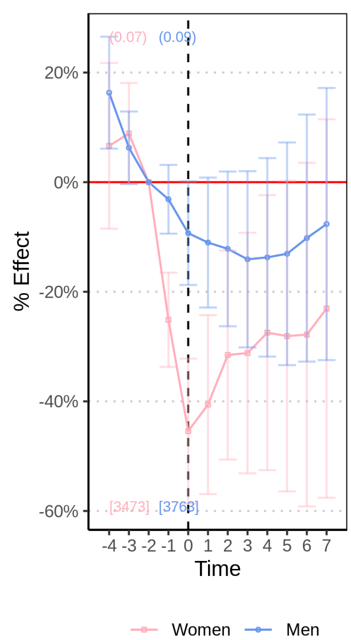
(b) Informal: LE



(c) Informal: HE



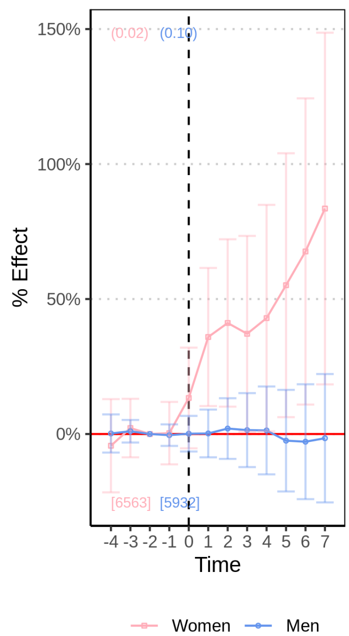
(d) Informal: Single



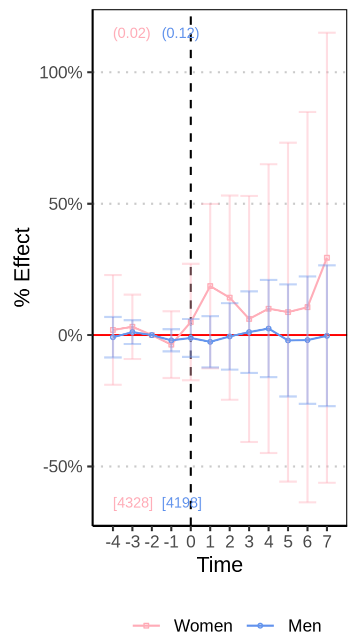
(e) Informal: Married

Note: Each graph plots the β_τ coefficients from Equation 2.1 as a percentage of the counterfactual outcome, together with 95% confidence intervals. The baseline coefficient is set at period -2. Numbers in parenthesis display the outcome variable level in the reference period and numbers in brackets the number of individuals in each analysis. LE stands for Low Educated and HE for highly educated. The outcome variable is a dummy variable for informal employment. Panel (a) uses the full samples, while panels (b)-(e) for sub-samples, respectively: low educated (high school or less), highly educated (some college or more), single and married.

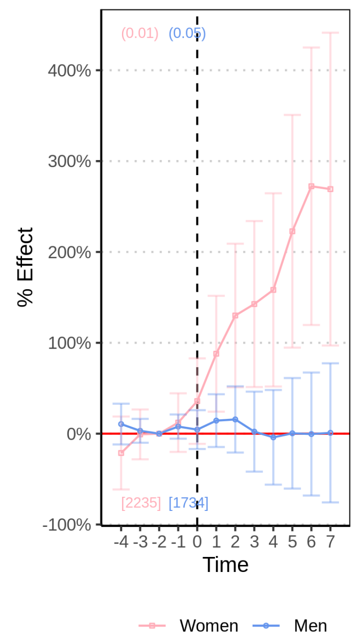
Figure 2.16: Self-Employment - Unconditional on Working



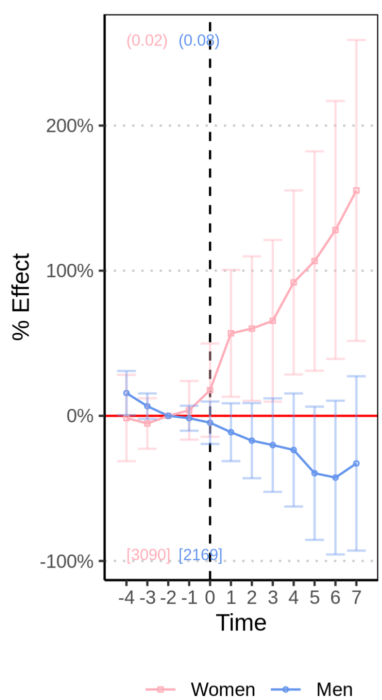
(a) Self-Employment: All



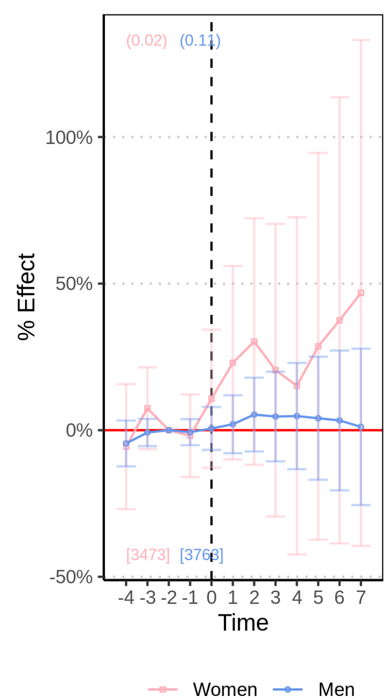
(b) Self-Employment: LE



(c) Self-Employment: HE



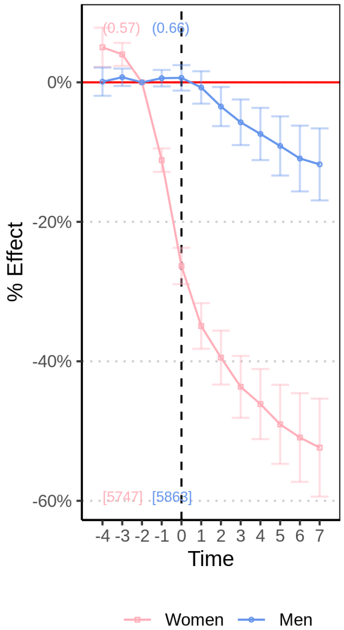
(d) Self-Employment: Single



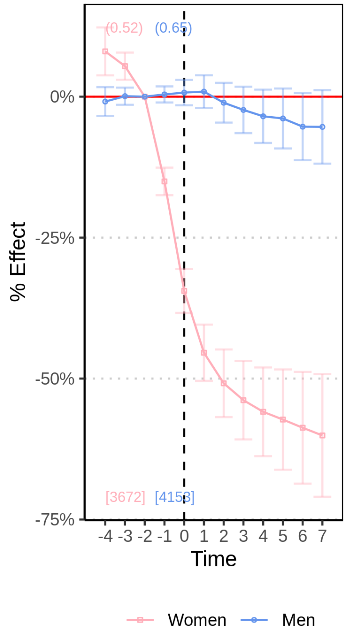
(e) Self-Employment: Married

Note: Each graph plots the β_τ coefficients from Equation 2.1 as a percentage of the counterfactual outcome, together with 95% confidence intervals. The baseline coefficient is set at period -2. Numbers in parenthesis display the outcome variable level in the reference period and numbers in brackets the number of individuals in each analysis. LE stands for Low Educated and HE for highly educated. The outcome variable is a dummy variable for self-employment. Panel (a) uses the full samples, while panels (b)-(e) for sub-samples, respectively: low educated (high school or less), highly educated (some college or more), single and married.

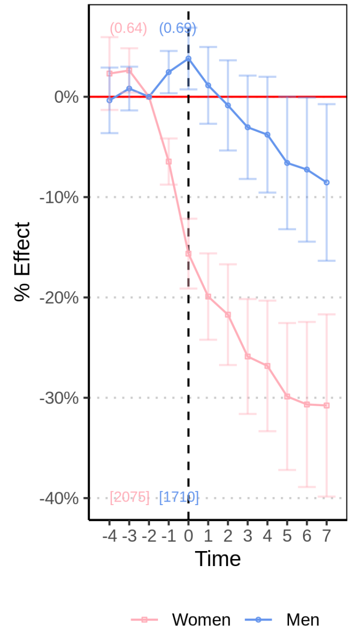
Figure 2.17: Pension Contribution - Unconditional on working



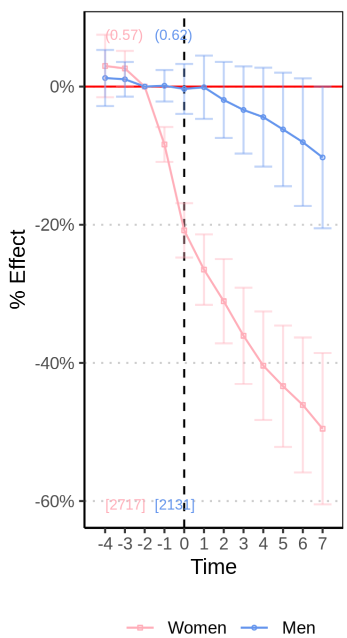
(a) Pension: All



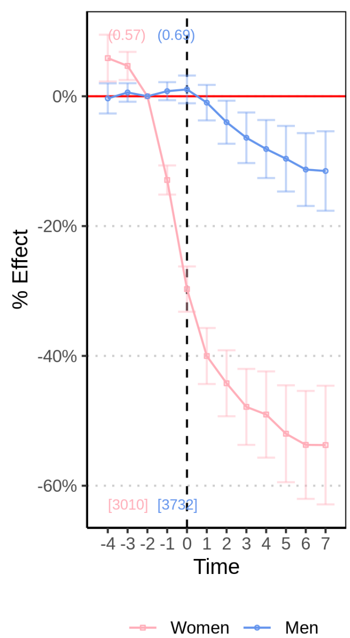
(b) Pension: LE



(c) Pension: HE



(d) Pension: Single



(e) Pension: Married

Note: Each graph plots the β_τ coefficients from Equation 2.1 as a percentage of the counterfactual outcome, together with 95% confidence intervals. The baseline coefficient is set at period -2. Numbers in parenthesis display the outcome variable level in the reference period and numbers in brackets the number of individuals in each analysis. LE stands for Low Educated and HE for Highly Educated. The outcome variable is a dummy variable for pension contribution (self-reported). Panel (a) uses the full samples, while panels (b)-(e) for sub-samples, respectively: low educated (high school or less), highly educated (some college or more), single and married.

Chapter 3

Maternal Mental Health and Children's Human Capital

(Joint with Paula Calvo and Zhengren Zhu)

3.1 Introduction

Mental health has become a focal point for public health discussions in the past decade. According to statistics from the Kaiser Family Foundation, over 30% of adults in the US report anxiety or depression symptoms, and 20% of them would need but are not receiving mental health therapy.[1] Two crucial characteristics of mental health disorders motivate this study. First, mental health issues begin early in a person's life cycle. In fact, 75% of mental health disorders begin before age 24, and 50% begin before age 14 (Kessler, Berglund, Demler, Jin, Merikangas, and Walters, 2005). Second, mental health is highly correlated with children's outcomes and socioeconomic status (Center on the Developing Child at Harvard University (2009)). These facts suggest that parents from lower socioeconomic blackgrounds and with mental health disorders may be more likely to raise children with poor

[1]From https://www.kff.org/interactive/mental-health-and-substance-use-state-fact-sheets/

mental health and lower skills, leading to a vicious cycle of poverty.

This paper proposes a model for the development of children's human capital, which subsumes children's cognitive skills and mental health. We focus on understanding the contribution of maternal mental health on her child's development, separately from the role of maternal cognitive and non-cognitive skills. The premise is that mental health is different from other non-cognitive abilities, such as self-esteem and self-control. In particular, we show that the correlation between maternal mental health and measures of non-cognitive skills, such as the Rosenberg Scale (self-steem) and Rotter-Locus Control Scale (self-control) is very low. We build on the rich child development literature that estimates production functions for children's human capital development to build our model (Cunha and Heckman (2007), Todd and Wolpin (2007), Cunha and Heckman (2008), Bernal (2008), Cunha, Heckman, and Schennach (2010), Del Boca, Flinn, and Wiswall (2014), Agostinelli and Wiswall (2016), Ronda (2017), Attanasio, Cattan, Fitzsimons, Meghir, and Rubio-Codina (2020a), Attanasio, Meghir, and Nix (2020b)). As in Attanasio, Cattan, Fitzsimons, Meghir, and Rubio-Codina (2020a) and Ronda (2017), we consider maternal mental health as a productive input. We differ from the former in that they measure cognitive and social skills of children when they are 12-24 months old, while we look at longer term outcomes in adolescence. In reference to the later, the author only focuses on children's cognitive skills while we also focus on children's mental health.[2] In addition, we consider three dimensions of maternal human capital: cognitive skills, non-cognitive skills and mental health.

This paper is motivated by important empirical patterns that we document using our data, the National Longitudinal Study of Youth 1979 (NLSY79) and the NLSY79

[2]In Ronda (2017) he measures child cognitive skills with the Letter-Word module of the Woodcock-Johnson aptitude test available from PSID. In our paper, we focus on PIAT Math and Reading Recognition tests available in NLSY79 Children and Young Adult.

Children and Young adults, which also describe key mechanisms in our model. First, maternal mental health disorders are positively associated with her child's mental health disorders and negatively associated with the child's cognitive development, even after controlling for household income, maternal education, mother's cognitive and non-cognitive abilities, along with other demographic controls. Second, poor maternal mental health is associated with worse parenting practices. This suggests that the interactions between the mother and her child are negatively affected when the mother has mental health problems, as she provides less emotional support and cognitive stimulation. Third, poor children's mental health affects their cognitive outcomes. These empirical facts have also been documented in the literature linking parental mental health, their children's outcomes and parental investments, and correlates of mental health in childhood (Caplan, Cogill, Alexandra, Robson, Katz, and Kumar (1989), Cummings and Davies (1994), Currie and Stabile (2007), Kiernan and Huerta (2008), Frank and Meara (2009), Mensah and Kiernan (2010), Mensah and Kiernan (2011), Letourneau, Tramonte, and Willms (2013), Dahlen (2016), Aizer, Stroud, and Buka (2016), Fitzsimons, Goodman, Kelly, and Smith (2017), Ronda (2017), Noonan, Burns, and Violato (2018), Persson and Rossin-Slater (2018), Bendini and Dinarte (2020), Kamis (2020), Baranov, Bhalotra, Biroli, and Maselko (2020)). Lastly, poor mental health in childhood is related to worse long term outcomes, including poor mental health in adulthood, lower educational attainment and lower wages. These results are consistent with previous findings in the literature (Z. Farmer (1993), Currie and Stabile (2007), Smith and Smith (2010), Goodman, Joyce, and Smith (2011)).

Equipped with these empirical facts, we incorporate them as key mechanisms of our model. In particular, we consider three channels of how maternal mental health can affect children. First, through a direct effect on children's cognitive skills and mental health. Second, maternal mental health affects their children's development through their ability in providing effective parenting. Third, as maternal mental health affects children's mental health, this may in turn affect the children's cognitive skills. We describe in detail the steps and the assumptions needed for the estimation of the structural parameters of our model, following Attanasio, Meghir, and Nix (2020b). We also suggest ways to control for the endogeneity of parental investments, to incorporate in later stages of this research.

The remaining of the paper is organized as follows. In the next section, we describe the data and empirical patterns related to the role mental health plays in the intergenerational transmission of socioeconomic status. Section 3.3 presents the human capital development model we use to synthesize the empirical patterns. Section 3.4 describes the procedure for estimating the human capital development model, and Section 3.5 concludes.

3.2 Empirical Evidence

3.2.1 Data

Data for our empirical analysis comes from the sample of young women from the National Longitudinal Survey of the Youth 1979 (NLSY79) and their children, who are part of the survey Child and Young Adults (NLSY79 Child/YA). This allows us to link the mothers with their children, but also to follow these children into adulthood, which is critical for our inter-generational analysis.

We focus our analysis on the cross-sectional sample of women, which consists of 3,108 individuals who were between 14 and 22 years old when interviewed for the first time in 1979.[3] We match them with their children, who were interviewed since

[3]We exclude from the analysis women and their children who are part of the Supplemental

1986. Moreover, starting in 1994, children aged 15 or older were interviewed with instruments similar to the ones used with their mothers.

The NLSY79 contains information on household demographics, such as age, education, race, marital status and income. More importantly, it includes information on cognitive, non-cognitive and mental health dimensions of respondents. The NLSY79 Child/YA contains rich assessments of the children, including test results, parenting practices, and behavioral problems. In the next subsection, we explain in detail all the variables we use in our analysis.

For most of the analysis, we use cross-sectional data of the year 1992, when mental health measures of women were collected for the first time. We limit our attention to children that were between 3 and 14 years old in that year. To assess long term outcomes, we augment our sample with information of the same children when they reach adulthood. These young adults were between 25 and 44 years old when last interviewed in 2016.

3.2.2 Evidence

The goal of this section is to document empirical patterns observed in the data, that describe mechanisms we incorporate in our model of children's human capital accumulation. In particular, we focus on the relation between maternal mental health, parental investments and children's outcomes (both cognitive and mental health outcomes). We also document the relation between the child's own mental health and their long-term outcomes as young adults, to highlight the importance of the intergenerational transmission of human capital. Before venturing into this objective, we present evidence that suggests that mental health is different from other dimensions of human capital, such as cognitive and non-cognitive skills. This fact encourages

Sample, over-sample of relatively disadvantaged individuals and the Military Sample.

the incorporation of maternal mental health as a different input into the children's human capital function.

What is mental health?

Previous studies examining the role of non-cognitive skills, as an input and as a dimension of human capital, use the term to summarize a set of skills not directly captured by standardized tests that measure cognitive skills, such as the Armed Forces Qualification Test (AFQT) (Humphries and Kosse, 2017). The most popular measures of non-cognitive skills include self-esteem, self-control, behavioral issues and risk and time preferences, among others. While one may argue that mental health seems only marginally related to these measures, we provide a formal approach by exploring the pairwise correlations between our measure of mental health and measures of cognitive and non-cognitive skills.

We follow the literature that measures non-cognitive skills and include the Rosenberg Scale, which is a measure of self-esteem, and the Rotter-Locus Control Scale, which measures self-control. We use AFQT as our measure of cognitive skills. To measure mental health, we use the Center for Epidemiologic Studies Scale (CES-D).[4] We standardize all measures to enable comparison.

The results in Table 3.1 suggest that correlations between mental health and non-cognitive skills range between -0.15 and -0.18. The pairwise correlation between the different measures of non-cognitive skills is larger in every case. The pairwise correlation between mental health and cognitive measures is -0.21, which is relatively low.[5] As we observe weak correlations between the mental health measure and

[4] A full description of the different scales for mental health, cognitive and non-cognitive measures can be found in Appendix 3.6.1.

[5] In Table 3.8 of Appendix 3.6.2, we explore the correlation between the components of the mental health measure and non-cognitive skills. Overall, the correlations are very weak. Table 3.9 shows that the correlations between mental health and non-cognitive measures are also low when we focus on the sample of NLSY79 women's young adult children. In addition, using data from

cognitive and non-cognitive skill measures, we consider mental health as an additional and separate dimension of human capital, departing from previous literature.

Table 3.1: Correlation between Mental Health, Cognitive and Non-Cognitive Measures

	CES-D Scale	Rosenberg Scale	Rotter-Locus Control Scale	AFQT
CES-D Scale	1.000			
Rosenberg Scale	-0.179	1.000		
Rotter-Locus Control Scale	-0.150	0.306	1.000	
AFQT	-0.213	0.293	0.310	1.000

Note: NLSY79 data. The sample includes 3,108 women. *CES-D Scale* is a 7-item depression measure. *Rosenberg Scale* is 10-item self-esteem measure. *Rotter-Locus Control Scale* includes four pairs of measures that capture self-control. *AFQT* includes arithmetic, word knowledge, paragraph comprehension and numerical operation scores from the ASVAB test.

Maternal Mental Health and Children Outcomes

In this section we study the intergenerational dimension of mental health. In particular, we examine the role that maternal mental health has on children's mental health and on a battery of children's cognitive outcomes. In addition, we empirically explore mechanisms through which maternal mental health affects children's development.

As mentioned above, our main measure of maternal mental health is CES-D. There is no equivalent measure of mental health for young children. Thus, we use instead six components of the dichotomous Behavioral Problem Index (BPI), related to children's different behaviors: antisocial, anxious, depressive, headstrong, hyperactive, and dependent.[6] As a robustness check, in part of the analysis we focus only

the Millennium Cohort Study in the United Kingdom, we find similar results as we observe weak correlations between mental health, non-cognitive and cognitive measures (not reported here but available upon request).

[6]According to the Center for Disease Control and Prevention (CDC), mental health disorders are "serious changes in the way children typically learn, behave or handle their emotions, which cause distress and problems getting through the day". Mental health disorders for children include, but are not limited to, anxiety, behavioral disorders, and attention deficit.

on the *Depression/Anxiety* components of the BPI.

We start by looking at the direct effect of maternal mental health on children's mental health. To eliminate as many confounding factors as possible, we control for demographic characteristics that could be correlated with maternal mental health and also affect our measure of children's mental health. In particular, all of our specifications control for the child's gender and age, maternal race and family income. Additionally, we control for the years of education of the mother and her marital status. We restrict most of our analysis to children in the age group of five to 14 years old.

Table 3.2 presents the results. In our main specification (Column (1)) we find a strong positive association between maternal mental health problems and her child's mental health disorders.[7] In Column (2), we show that the results are robust when we restrict our attention only to the depression/anxiety sub-components of the BPI. Specifically, our results suggest that a one standard deviation improvement in maternal mental health is associated with a 0.24 standard deviation improvement in her child's mental health.[8] The specification in Column (3) further controls for non-cognitive maternal skills. Our results suggest a much lower correlation between a child's mental health disorders and her maternal non-cognitive skills, relative to the correlation between a child's mental health disorders and maternal mental health problems.[9]

[7]Our results are consistent with the findings of Frank and Meara (2009), although they have different regression specifications and a different measure of maternal mental health. They consider maternal depression in the following way: a depressed woman is such that scores 16 or higher in the 1992 CES-D assesment in NLSY79. In our case, we consider the continuous standardized measure of CES-D as our measure of mental health.

[8]We perform a similar analysis using data from the Millennium Cohort Study in the UK. Our results (available upon request) suggest that for children with ages 3 to 14 years old, a one standard deviation improvement in parental mental health is associated with a 0.30 standard deviation improvement in the child's mental health.

[9]The coefficients of the non-cognitive measures remain mainly unchanged in magnitude when we *exclude* maternal mental health from Column (3) in Table 3.2.

Table 3.2: Maternal Mental Health and Children's Mental Health

	(1) Child Mental Disorders (BPI)	(2) Depression/Anxiety	(3) Child Mental Disorder (BPI)
Maternal Mental Health Disorders	0.282***	0.239***	0.266***
	(0.026)	(0.026)	(0.027)
Log Household Income	-0.085*	-0.041	-0.068
	(0.046)	(0.038)	(0.045)
Mother's Years of Education	-0.047***	-0.003	-0.036***
	(0.012)	(0.013)	(0.012)
Maternal Rosenberg Scale			-0.094***
			(0.028)
Maternal Rotter-Locus Scale			-0.031
			(0.027)
Child's age group	5-14 yo	5-14 yo	5-14 yo
Demographic Controls	Yes	Yes	Yes
R-squared	0.126	0.092	0.136
Observations	1,519	1,519	1,519

Note: NSLY79 and NLSY79 Child/YA, cross-sectional sample from 1992. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions control for child's gender and age, maternal race and marital status. *Maternal Mental Health Disorders* measured by CES-D Depression Scale. *Children's Mental Health Disorders* measured by the Behavioral Problem Index. *Maternal Rosenberg Scale* is a 10-item self-esteem measure. *Maternal Rotter-Locus Scale* captures self-control.

There are multiple potential mechanisms through which maternal mental health disorders are transmitted to her child. First, there is the biologically rooted explanation where certain genetic markers are correlated with mental health, and these are transmitted to children at birth (Center on the Developing Child at Harvard University (2009)). Second, mental health of mothers may directly affect the formation of their children's mental health through their ability of providing effective parenting. Third, maternal mental health may also affect her child's cognitive abilities through the effect of the child's mental health on the accumulation of cognitive skills.

We use three measures associated with family environment and parenting to show that maternal mental health matters for parenting investments: the *home inventory index*, *parental emotional support* and *parental cognitive stimulation.*[10] Table 3.3

[10]See Appendix 3.6.1 for detailed information on how these measures are built for children at different ages.

presents the results based on the home inventory index for children of different ages. Our results show a consistent pattern: worse maternal mental health is associated with worse parenting practices, for children of ages 3 to 14 years old.[11] In these specifications, we control for non-cognitive skills of the mother and we observe that maternal mental health and non-cognitive skills measured by the Rosenberg Scale are both statistically significant. We report the results for the sub-components, cognitive stimulation and emotional support, in Appendix 3.6.2 (Tables 3.10 and 3.11) and we find similar results for both dimensions.[12]

Table 3.3: Maternal Mental Health and Parenting Practices

	Home Inventory	Home Inventory	Home Inventory
Maternal Mental Health Disorders	-0.116***	-0.100***	-0.079***
	(0.044)	(0.031)	(0.028)
Maternal Rosenberg Scale	0.111**	0.098***	0.193***
	(0.043)	(0.036)	(0.034)
Maternal Rotter-Locus Scale	0.016	0.060	0.060**
	(0.039)	(0.037)	(0.030)
Child's age group	3-5	6-9	10-14
Demographic variables	Yes	Yes	Yes
R-squared	0.315	0.308	0.368
Observations	547	741	697

Note NSLY79 and NLSY79 Child/YA, cross-sectional sample from 1992. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. All regressions control for household income, child's gender, maternal race and education, and her marital status. *Maternal Mental Health Disorders* measured by the CES-D Depression Scale. *Maternal Rosenberg Scale* is a 10-item self-esteem measure. *Maternal Rotter-Locus Scale* captures self-control. *Home Inventory* is a measure of parental practices.

[11] In most of our analysis we focus on the sample of children ages 5 to 14 years old. For these children we have information on the BPI but also on tests scores. However, we have information on parenting practices starting at 3 years old and our measures of parenting practices are different for the age groups 3 to 5 years old, 6 to 9 and 10 to 14 years old. To increase the sample size in our group of young children, we focus on the pooled sample of 3 to 5 years old when studying parenting practices. When studying test scores, we pool children of ages 5 to 9. Results remain unchanged when we exclude 5-year-old children from our analysis of test scores.

[12] Our results differ from Frank and Meara (2009), where they also use NLSY79 data. In their case, they do not find significant results for cognitive stimulation. As mentioned before, it can be due to different regressions specifications and definitions of maternal mental health. In another study for the U.S., using PSID data, Ronda (2017) also finds that maternal distress affects maternal time investments.

We go one step further and confirm that parenting practices matter for a child's mental health. In Table 3.4, we report that a one standard deviation improvement in home inventory, our aggregated measure of parenting practices, is associated with a 0.29 to 0.31 standard deviation improvement in a child's mental health. We show the results for the index subcomponents in Appendix 3.6.2 (Tables 3.12 and 3.13), where we report similar results across the two dimensions.[13]

Table 3.4: Parenting Practices and Children's Mental Health

	(1) Child Mental Health Disorders	(2) Child Mental Health Disorders	(3) Child Mental Health Disorders
Home Inventory	-0.306***	-0.285***	-0.296***
	(0.051)	(0.045)	(0.050)
Child's age group	3-5	6-9	10-14
Demographic variables	Yes	Yes	Yes
R-squared	0.159	0.121	0.090
Observations	391	746	703

Notes: NSLY79 and NLSY79 Child/YA, cross-sectional sample from 1992. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions control for household income, child's gender, maternal race and education, and marital status. *Child Mental Health Disorders* measured by the Behavioral Problem Index. *Home Inventory* is a measure of parental practices.

We move now to report the relationship between maternal mental health and children's cognitive outcomes. We focus here in cognitive outcomes early in the life of children, before they enter college or the labor market. As a measure of a child's cognition, we use the Peabody Individual Achievement Tests (PIAT) for Math and Reading Recognition. One mechanism through which maternal mental health might

[13] In non-reported results, we also use the Millennium Cohort Study sample to test a similar hypothesis, associated with how mental health problems are associated with a worse family environment. We find that worse parental mental health increases conflict between parents and children, and decreases closeness between them. Moreover, we find that these effects may have significant implications on a child's mental health: a one standard deviation increase in parent-child conflict is associated with a 0.49 standard deviation increase in children's mental health problems, whereas a one standard deviation increase in parent-child closeness is associated with a 0.24 standard deviation decrease in children's mental health problems. These results are available upon request.

affect her child's cognitive outcomes is the child's own mental health. We explore then the relationship between a child's own mental health and cognitive outcomes and report the results in Table 3.5. We report that a child's poor mental health is correlated with lower test scores. More specifically, one standard deviation increase in mental health disorders is associated with a 0.07 standard deviation decrease in cognitive outcomes of children ages 5 to 9 (Columns (1) and (2)).[14][15] The effects are larger for older children (Columns (3) and (4)). As a comparison, this effect is equivalent to that of a 2-4 year decrease in maternal education.[16]

Table 3.5: Children's Mental Health and Cognitive Outcomes

	(1) Math Score	(2) Reading Score	(3) Math Score	(4) Reading Score
Child Mental Health Disorders	-0.072***	-0.066***	-0.101***	-0.104***
	(0.017)	(0.016)	(0.019)	(0.025)
Child's age group	5-9 yo	5-9 yo	10-14 yo	10-14 yo
Demographic Controls	Yes	Yes	Yes	Yes
R-squared	0.623	0.613	0.278	0.310
Observations	836	815	599	600

Notes: NSLY79 and NLSY79 Child/YA, cross-sectional sample from 1992. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions control for household income, child's gender, maternal race and education and her marital status. *Child Mental Health Disorders* measured by the Behavioral Problem Index. *Math Score* from Math PIAT Score. *Reading Score* from Reading Recognition PIAT Score.

The previous results suggest that maternal mental health disorders may lead to worse children's cognitive skills via children's mental health. We then explore whether there are other mechanisms through which maternal mental health affect children outcomes. We do this by adding controls for maternal mental health and parenting practices to our specification in Table 3.5 (reported in Table 3.6). We

[14] As mentioned before, since the PIAT tests are only implemented to children ages 5 and over, we do not report here the age group 3-5 separately. Instead we decided to pool children ages 5 to 9 to increase the sample size and do not lose information on the younger children.

[15] These results are consistent with the findings in Currie and Stabile (2007), where they study the relation between children's mental health and their cognitive development using the same instruments. We have a slight different set of controls in our regressions.

[16] We find similar effects on the Millennium Cohort Study sample (results available upon request).

observe that for younger children, good parenting offsets about half of the negative impacts of own mental health problems on cognitive outcomes, pointing to an additional channel through which maternal mental health operates. There are no additional *direct* effects of maternal mental health, after controlling for a child's own mental health and parenting practices. However, for older children, maternal mental health has a negative impact on cognitive outcomes, even after controlling for parenting practices, the child's own mental health disorders and maternal non-cognitive skills.[17] Then, it is not only the case that maternal mental health hinders the cognitive development of children by affecting their mental health, but also has a direct negative impact that offsets the positive effect of good parenting. These results are in line with the findings of Ronda (2017) but differ from Frank and Meara (2009). We find consistent effects when we focus on the subcomponents of the Home Inventory Index, Emotional Support and Cognitive Stimulation (Table 3.16 in Appendix 3.6.2.)

[17]We also report results for Reading Recognition (PIAT) on Appendix 3.6.2 Table 3.14, where we observe analogous results. As a robustness specification, we run the same regressions excluding children's own mental health and home inventory, and we report that maternal mental health is significantly related to math and reading recognition at ages 10-14 (results in Appendix 3.6.2 Table 3.15).

Table 3.6: Parenting Practices, Maternal Mental Health, and Cognitive Development

	(1) Math Score	(2) Math Score
Home Inventory	0.036*	0.068**
	(0.019)	(0.026)
Child Mental Health Disorders	-0.071***	-0.086***
	(0.019)	(0.019)
Maternal Mental Health Disorders	0.032	-0.047***
	(0.021)	(0.019)
Maternal Rosenberg Scale	0.019	-0.011
	(0.018)	(0.023)
Maternal Rotter-Locus Scale	0.024	0.034
	(0.018)	(0.025)
Child's age group	5-9 yo	10-14 yo
Demographic Controls	Yes	Yes
R-squared	0.625	0.342
Observations	776	610

Notes: NSLY79 and NLSY79 Child/YA, cross-sectional sample from 1992. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions control for household income, child's gender, maternal race and education and her marital status. *Child Mental Health Disorders* measured by the Behavioral Problem Index. *Maternal Mental Health Disorders* measured by the CES-D Depression Scale. *Math Score* from Math PIAT Score.

Mental Health and Adult Outcomes

Finally, to close the inter-generational cycle, we explore the relation between a child's mental health and her adult outcomes. We consider three measures of adult outcomes: whether they have a college degree, the average real wages between ages 25 and 35, and mental health at the onset of adulthood (age 18). For this analysis, we pool information on children that were 5 to 14 years old in 1992. We control for demographic characteristics of a child's household in that year.

We report our results in Table 3.7. We observe that children's mental health disorders are associated with worse outcomes in adulthood. A reduction of one standard deviation in a child's mental health is associated with 6.1 percentage points lower chances of completing college education, a 15% decrease in mean wages in early adulthood and an increase of 0.43 standard deviations in our mental health disorder index at age 18.[18] In Table 3.17 in Appendix 3.6.2 we focus on children aged 10 to 14 years old and show that the negative impacts of mental health on long-term outcomes persist even when we control for children's cognitive outcomes.

Table 3.7: Children's Mental Health and Long-term Outcomes

	(1) College attainment	(2) Wages (log)	(3) Adult Mental Disorder
Child Mental Health Disorder	-0.061***	-0.150***	0.427***
	(0.012)	(0.029)	(0.115)
Child's age group (in 1992)	5-14 yo	5-14 yo	5-14 yo
Demographic Controls	Yes	Yes	Yes
Observations	1,565	1,347	825
R-squared	0.116	0.147	0.043

Notes: NSLY79 and NLSY79 Child/YA, cross-sectional sample from 1992. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions control for household income, child's gender, maternal race and education, and her marital status. *Child Mental Health Disorders* measured by the Behavioral Problem Index. *Adult Mental Health Disorders* measured by the CES-D Depression Scale.

3.3 Model

The empirical results presented above depict a complex system through which poor maternal mental health can lead to poor outcomes on children, both in the short and in the long run. There are three potential mechanisms underlying this intergenerational pattern. First, poor mental health of children could be a direct result of poor maternal mental health. Second, maternal mental health may affect parenting practices that, in turn, affect children's mental health and cognitive skills. Third, as maternal mental health affects her child's mental health, the latter can also affect the accumulation of cognitive skills.

[18] As expected, results are quantitatively larger in most dimensions when we focus on the sample of children aged 10 to 14 in 1992. However, even mental health disorders early in life (ages 5 to 9) have detrimental long term consequences (results available upon request).

In addition, the empirical patterns suggest the importance of treating mental health as a related but independent measure of human capital. We consider three dimensions of human capital — mental health, non-cognitive skills, and cognitive skills — for adults. In the case of children, due to data constraints, we only consider children's mental health and cognitive skills as their dimensions of human capital. We provide a framework under which we can potentially disentangle the various mechanisms described previously: we build a model of human capital development of children where the inputs in the production function are children's past cognitive skills and mental health, maternal skills and mental health, and parental investments.

3.3.1 Production Function of Children's Human Capital

We follow Attanasio, Cattan, Fitzsimons, Meghir, and Rubio-Codina (2020a) and assume that the technology for skill formation is Cobb Douglas. This allows each of the human capital measures — cognitive skills, non-cognitive skills, and mental health — to be affected by parental investments, maternal skills and by past human capital measures.[19] In particular, we denote a child's cognitive skills and mental health at time t as $\theta^c_{i,t}, \theta^m_{i,t}$, respectively. We indicate maternal cognitive skills, non-cognitive skills and mental health as $\theta^{P,c}_i, \theta^{P,n}_i$ and $\theta^{P,m}_i$, respectively. For $k \in \{c, m\}$, children's human capital $\theta^k_{i,t}$ is produced by:

$$\ln(\theta^k_{i,t+1}) = \alpha_{0,k} + \sum_k \alpha^{ch}_k \ln(\theta^k_{i,t}) + \sum_j \alpha^p_j \ln(\theta^{P,j}_i) + \alpha_1 \ln(\theta^I_{i,t}) + \varepsilon^k_{i,t+1} \qquad (3.1)$$

where $\theta^{P,j}_i$ is a parental measure of skill j, where $j \in \{c, n, m\}$ denotes cognitive skills, non-cognitive skills and mental health, respectively. These measures are as-

[19]Notice that this specification not only allows children's mental health to affect their cognitive ability, but also allows previous cognitive ability to affect their mental health. This is a plausible mechanism, as students who perform poorly in school might suffer from anxiety about school performance.

sumed fixed across time periods. The term $\theta^I_{i,t}$ represents parental investments, which capture parenting support.[20] The last term $\varepsilon^k_{i,t+1}$ reflects unobserved random shocks that affect the child's development.

Parental investments is an endogenous object in our model:

$$\ln(\theta^I_{i,t}) = \beta_0 + \sum_k \beta^{ch}_k \ln(\theta^k_{i,t}) + \sum_j \beta^p_j \ln(\theta^{P,j}_i) + \beta_1 X_{i,t} + \eta_{i,t+1} \tag{3.2}$$

The empirical specification of investment in the model depends on the current cognitive skills and mental health of the child, maternal cognitive and non-cognitive skills, maternal mental health, household or parental characteristics $X_{i,t}$ and random shocks $\eta_{i,t+1}$. The family background characteristics include household income, maternal marital status, maternal education and race. Parental investments can be endogenous in the sense that mothers react to shocks in the development of their children's human capital, for instance, to compensate for a negative health shock. In order to account for this potential endogeneity of investments in the estimation of the parameters of the production function, in next steps in this paper, we plan to incorporate prices for child investments (including books, materials for school, toys, childcare, among others, at the state geographic level).[21]

The model for human capital production described above captures the mechanisms of intergenerational transmission of human capital previously described. The mental health of the mother could affect children's outcomes through α^p_m. Maternal mental health, non-cognitive skills and cognitive skills may also affect parenting investments through Equation 3.2 and, in turn, affect children outcomes through α_1. Finally, the stock of children's cognitive skills and mental health affects human

[20]For estimation purposes, we consider measures related to cognitive stimulation and emotional support.

[21]In Attanasio, Meghir, and Nix (2020b) the authors consider prices for food, medications, educational goods and clothing at the local level.

capital development through α_k^{ch}.

3.4 Estimation

A key difficulty in estimating factor models is that we do not observe skills, mental health or investments ($\theta_{i,t}^k$, $\theta_{i,t}^{P,j}$ or $\theta_{i,t}^I$ for $k \in \{c, nc\}$ and $j \in \{c, nc, m\}$), but instead we observe imperfect measures. Our objective is to identify the distribution of the latent factors using observed measures. We follow Attanasio, Meghir, and Nix (2020b) and their assumptions to estimate the parameters of interest.

Denote the l-th measure of latent factor s at time t as m_{itl}^s. The measures follow the relationship:

$$m_{itl}^s = a_{tl}^s + \lambda_{tl}^s \ln \theta_{it}^s + \epsilon_{itl}^s \tag{3.3}$$

where the errors ϵ_{itl}^s are iid normal with $\epsilon_{itl}^s \sim N(0, \sigma_{itl}^s)$. The measurement system is expressed as follows in matrix form:

$$M_i = A + \Lambda \ln \theta_i + \Sigma \epsilon_i \tag{3.4}$$

where A is the collection of all location parameters a_{tl}^s and Λ is the matrix of factor loadings λ_{tl}^s, with the (m, n) element being the factor loading of the n-th factor on the m-th measure. Σ is a diagonal matrix collecting all σ_{itl}^s on the diagonal.

One of the assumptions is that the log latent factors follow a mixed normal distribution:

$$F_\theta = \tau * \Phi(\mu_A, \Omega_A) + (1 - \tau) * \Phi(\mu_B, \Omega_B) \tag{3.5}$$

where $\tau \in (0, 1)$. Considering the measurement system in Equation 3.4, the measures also follow a mixed normal distribution:

$$M_i \sim F_M = \tau\Phi(\Pi_A, \Psi_A) + (1-\tau)\Phi(\Pi_B, \Psi_B) \tag{3.6}$$

where

a. $\Pi_A = A + \Lambda\mu_A$

b. $\Pi_B = A + \Lambda\mu_B$

c. $\Psi_A = \Lambda\Omega_A\Lambda' + \Sigma$

d. $\Psi_B = \Lambda\Omega_B\Lambda' + \Sigma$

The parameters in the mixed normal distribution of the measures, $\{\Pi_A, \Psi_A, \Pi_B, \Psi_B, \tau\}$, can be directly estimated using MLE since the measures are observed. This step is implemented using the Expectation Maximization (EM) algorithm. For the identification of the parameters of the underlying factors' distribution in Equation 3.5 and of the measurement Equation 3.4, we also follow the assumptions in Attanasio, Meghir, and Nix (2020b):

- Assumption 1 (Normalization of Scale): $\lambda^s_{it1} = 1$ for all i, t, s.

- Assumption 2 (Mean Zero): $\tau * \mu^s_{A1} + (1-\tau) * \mu^s_{B1} = 0$. Here, we impose a restriction on the mean of the log factor s at time 1. For one-period measures (for instance, maternal mental health), the mean of the log will be zero. For evolving factors, we only normalize the location for the first period.

- Assumption 3 (Time Invariance): $a^s_{tl} = a^s_{t'l}$ for all t and t'. This restriction allows identification of the location of the factors.

Overall, the estimated parameters $\{\Pi_A, \Psi_A, \Pi_B, \Psi_B, \tau\}$, the assumptions stated above and the restrictions in (a)-(d), provide sufficient restrictions to estimate the remaining parameters using minimum distance: $A, \Lambda, \Sigma, \mu_A, \mu_B, \Sigma_A$ and Σ_B. Once we recover the parameters, we draw a synthetic data set to estimate the model using regressions, generating estimates for the production function of children's cognitive skills and mental health as well as investment functions.

Given the estimation results on the importance of maternal mental health and parental investments for the accumulation of children's human capital, we will generate policy counterfactuals that address improvements in these dimensions. We plan to conduct two type of exercises: in the first one, we would explore the impact of ameliorating the mental health of the mothers by the average effect of successful programs, such as cognitive behavioral therapy, that targets maternal depression or anxiety. We could evaluate the effect of such interventions at different stages in childhood or in the adolescence. In the second type of exercises, we would analyze the effect of improving parenting practices at different ages of the child's life and for children from different economic backgrounds.

3.5 Conclusion

In this paper, we examine the role maternal mental health plays in the human capital development of children, which subsumes cognitive skills and mental health. We propose a model for the development of children's human capital, where maternal human capital is characterized by three dimensions: cognitive skills, non-cognitive skills and mental health. In addition, parental investments and the child's own skills are productive inputs in this model. This setting is motivated by empirical patterns we observe in the U.S., which will also be the key mechanisms in our model.

First, poor maternal mental health is positively related with her child's poor mental health and negatively associated with her child's cognitive development. Second, maternal mental health problems are associated with worse parenting practices, such as emotional support and cognitive stimulation. Third, poor children's mental health is related to lower children's cognitive outcomes during school age. We describe the estimation steps and potential policy counterfactual exercises that allows us to learn about the importance of mental health for the intergenerational transmission of poverty, as children's mental health is positively correlated with long-term outcomes, such as wages, education and mental health.

In future research, an extension of this model would include a measure of physical health as a dimension of human capital. For such analysis, we would require rich measures of health that include, for example, obesity, and bio-metrics such as cholesterol, blood pressure and sugar levels in blood and measures of parental investments in quality of food intakes. This would be of particular relevance for the U.S., where the prevalence of obesity was 42% in adults in 2017-2018 and around 10.5% of the U.S. population have diabetes (Hales, Carroll, Fryar, and Ogden (2020)).[22]

[22]Information on diabetes available at: https://www.cdc.gov/diabetes/data/statistics-report/index.html

3.6 Appendix

3.6.1 Scales

In this section, we describe the scales used to proxy for cognitive skills, non-cognitive skills and mental health. In this paper we use two data sets: NLSY79 and NLSY79 Child/YA, linking children and their mothers.

Scales for adults (NLSY79)

For mothers, we proxy cognitive skills using AFQT (Armed Forces Questionnaire Test), non-cognitive skills using the Rosenberg Scale and Rotter-Locus Scale, and mental health using the CES-D Scale (Center for Epidemiologic Studies Depression Scale).

- AFQT: We use the AFQT score reported at NLSY79, which is computed using the arithmetic reasoning, word knowledge, paragraph comprehension and numerical operations components of the ASVAB test.

- Rosenberg Scale: This is a measure of self-esteem, a scale that includes the following 10 items.

  1. I am person of worth.
  2. I have a number of good qualities.
  3. I am inclined to feel I am a failure.
  4. I am able to do things as well as most other people.
  5. I felt I do not have much to be proud of.
  6. I take a positive attitude toward myself.

7. I am satisfied with myself.

8. I wish I could have more respect of myself.

9. I certainly feel useless at times.

10. At times I think I am no good at all.

- Rotter-Locus Control Scale: This captures whether individuals believe they have control over their lives or it is the environment that controls their lives. It includes the following four pair of statements.

  1. Degree of control the respondent has over her direction of own life.
  2. Importance of planning.
  3. Importance of luck.
  4. Degree of influence over own life.

- CES-D Scale: This scale measures depression, and includes seven statements on how they felt during the week prior to the interview.

  1. I felt depressed.
  2. I felt sad.
  3. I could not get going.
  4. I did not feel like eating.
  5. I had trouble keeping my mind on what I was doing.
  6. I felt everything I did was an effort.
  7. My sleep was restless.

Scales for children (NLSY79 Child/YA)

- Behavioral Problem Index (BPI): We construct this variable using the following components.

  1. Antisocial
  2. Headstrong
  3. Anxious/Depressed
  4. Hyperactive
  5. Peer Problems
  6. Dependent

  Higher values of the components represent a higher level of behavioral disorders.[23]

- Depression/Anxiety: We construct this measure using only the Anxiety/Depression component of the BPI. This measure is based on the following five sub-components:

  1. Has sudden changes in mood of feeling.
  2. Feels/complains no one loves her/him.
  3. Is too fearful or anxious.
  4. Feels worthless or inferior.
  5. Is unhappy, sad, or depressed.

- Peabody Individual Achievement Test (PIAT) for Math and Reading Recognition: This test is applied on children who are at least five years old. Results

[23] The individuals components of each category and a more complete description can be found in `https://www.nlsinfo.org/content/cohorts/nlsy79-children/other-documentation/codebook-supplement/appendix-d-behavior-proble-0`.

are based on the raw scores of the assessments, standardized to a normal with mean zero and standard deviation of one.[24]

Parenting Practices (NLSY79 Child/YA)

- Home Observation Measurement of the Environment (HOME): It is a measure of the quality of a child's home environment, it includes two main components: emotional support and cognitive stimulation.[25]

- Cognitive Stimulation: This component measures parental practices that promote cognitive development, including reading stories, helping the child with numbers and shapes, taking the child to museum or outings, among others.

- Emotional Support: This component measures practices that promote emotional support and include, for example, parental practices when the child is angry, hugging and answering the child's requests verbally, among others.

3.6.2 Descriptive Evidence

Table 3.8: Correlation between the components of Mental Health and Non-Cognitive Measures

	Depression	Sad	Can't keep going	Poor appetite	Cannot focus	Extra Effort	Restless
Rosenberg Scale	-0.187	-0.131	-0.130	-0.093	-0.119	-0.124	-0.078
Rotter-Locus Scale	-0.115	-0.089	-0.107	-0.103	-0.097	-0.128	-0.081

Note: Data from NLSY79. Sample includes 3,108 women. The *CES-D* measure is composed of 7 items: feels depressed, feels sad, cannot get going, does not feel like eating, has trouble keeping her mind on what she is doing, feels everything she does is an effort and sleep is restless. *Rosenberg Scale* is 10-item self-esteem measure. *Rotter-Locus Control Scale* includes four pairs of measures that capture self-control.

[24] More information on the PIAT assessment is available at: `https://www.nlsinfo.org/content/cohorts/nlsy79-children/topical-guide/assessments/piat-mathematics`.

[25] A complete list of the components of HOME from ages three to five is available at: `https://www.nlsinfo.org/content/cohorts/nlsy79-children/other-documentation/codebook-supplement/appendix-home-sf-scales/page/0/2/#AppendixA2B`.

Table 3.9: Correlation between Mental Health, Cognitive and Non-Cognitive Measures (Sample NLSY79 Child/YA)

	Mental Health (CES-D)	Rosenberg Scale	Pearlin Scale	BIG-5 Personality Traits
Mental Health (CES-D)	1.000			
Rosenberg Scale 2004	-0.301	1.000		
Pearlin Scale 2004	-0.305	0.651	1.000	
BIG5 Personality Traits	-0.174	0.248	0.247	1.000

Note: Data from NLSY79 Child/YA, at year 2004. Sample includes 2,431 young adults, who are between 15 and 25 years old. The *CES-D* measure is composed of 7 items: feels depressed, feels sad, cannot get going, does not feel like eating, has trouble keeping her mind on what she is doing, feels everything she does is an effort and sleep is restless. *Rosenberg Scale* is 10-item self-esteem measure. *Pearlin Scale* measures self-concept and whether individuals perceive their are in control of events that affect their lives. *Big-5 Personality Traits* measure openness, conscientiousness, extraversion, agreeableness and neuroticism.

Table 3.10: Maternal Mental Health and Emotional Support

	(1) Emotional Support	(2) Emotional Support	(3) Emotional Support
Maternal Mental Health Disorders	-0.094**	-0.110***	-0.096***
	(0.043)	(0.033)	(0.034)
Maternal Rosenberg Scale	0.107**	0.062	0.101***
	(0.044)	(0.041)	(0.038)
Maternal Rotter-Locus Scale	-0.021	0.004	0.064*
	(0.043)	(0.040)	(0.035)
Child's age group	3-5	6-9	10-14
Demographic variables	Yes	Yes	Yes
R-squared	0.194	0.265	0.299
Observations	523	680	612

Note: NSLY79 and NLSY79 Child/YA, cross-sectional sample from 1992. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions control for household income, child's gender, maternal race and education, and her marital status. *Maternal Mental Health Disorders* measured by the CES-D Depression Scale. *Emotional Support* is a sub-component of the HOME Inventory for parental practices.

Table 3.11: Maternal Mental Health and Cognitive Stimulation

	(1) Cognitive Stimulation	(2) Cognitive Stimulation	(3) Cognitive Stimulation
Maternal Mental Health Disorders	-0.096**	-0.061*	-0.034
	(0.047)	(0.034)	(0.032)
Maternal Rosenberg Scale	0.059	0.090**	0.203***
	(0.051)	(0.035)	(0.038)
Maternal Rotter-Locus Scale	0.064	0.095**	0.035
	(0.043)	(0.037)	(0.033)
Child's age group	3-5	6-9	10-14
Demographic variables	Yes	Yes	Yes
R-squared	0.236	0.252	0.260
Observations	522	707	690

Note: NSLY79 and NLSY79 Child/YA, cross-sectional sample from 1992. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions control for household income, child's gender, maternal race and education, and her marital status. *Maternal Mental Health Disorders* measured by the CES-D Depression Scale. *Cognitive Stimulation* is a sub-component of the HOME Inventory for parental practices.

Table 3.12: Emotional Support and Children's Mental Health

	(1) Child Mental Health Disorders	(2) Child Mental Health Disorders	(3) Child Mental Health Disorders
Emotional Support	-0.241***	-0.129***	-0.257***
	(0.053)	(0.043)	(0.050)
Child's age group	3-5	6-9	10-14
Demographic variables	Yes	Yes	Yes
R-squared	0.130	0.076	0.092
Observations	373	689	610

Note: NSLY79 and NLSY79 Child/YA, cross-sectional sample from 1992. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions control for household income, child's gender, maternal race and education, and her marital status. *Child Mental Health Disorders* measured by the Behavioral Problem Index. *Emotional Support* is a sub-component of the HOME Inventory for parental practices.

Table 3.13: Cognitive Stimulation and Children's Mental Health

	(1) Child Mental Health Disorders	(2) Child Mental Health Disorders	(3) Child Mental Health Disorders
Cognitive Stimulation	-0.245***	-0.308***	-0.190***
	(0.053)	(0.043)	(0.048)
Child's age group	3-5	6-9	10-14
Demographic variables	Yes	Yes	Yes
R-squared	0.134	0.131	0.063
Observations	371	715	695

Note: NSLY79 and NLSY79 Child/YA, cross-sectional sample from 1992. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions control for household income, child's gender, maternal race and education, and her marital status. *Child Mental Health Disorders* measured by the Behavioral Problem Index. *Cognitive Stimulation* is a sub-component of the HOME Inventory for parental practices.

Table 3.14: Parenting Practices, Maternal Mental Health, and Cognitive Development (Reading)

	(1) Reading Score	(2) Reading Score
Home Inventory	0.048***	0.060*
	(0.018)	(0.031)
Child Mental Health Disorders	-0.058***	-0.089***
	(0.017)	(0.026)
Maternal Mental Health Disorders	0.013	-0.085***
	(0.017)	(0.027)
Maternal Rosenberg Scale	0.019	0.016
	(0.018)	(0.028)
Maternal Rotter-Locus Scale	0.007	0.028
	(0.017)	(0.027)
Child's age group	5-9 yo	10-14 yo
Demographic Controls	Yes	Yes
R-squared	0.620	0.353
Observations	756	611

Note: NSLY79 and NLSY79 Child/YA, cross-sectional sample from 1992. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions control for household income, child's gender, maternal race and education, and her marital status. *Child Mental Health Disorders* measured by the Behavioral Problem Index and *Maternal Mental Health Disorders* measured by the CES-D Depression Scale. *Reading Score* from Reading Recognition PIAT Score. *Home Inventory* is a measure of parental practices. *Maternal Rosenberg Scale* is a 10-item self-esteem measure. *Maternal Rotter-Locus Scale* captures self-control.

Table 3.15: Maternal Mental Health and Cognitive Development (Math and Reading)

	(1) Math Score	(2) Math Score	(3) Reading Score	(4) Reading Score
Maternal Mental Health Disorders	-0.005	-0.074***	-0.008	-0.105***
	(0.019)	(0.017)	(0.018)	(0.023)
Child's age group	5-9 yo	10-14 yo	5-9 yo	10-14 yo
Demographic Controls	Yes	Yes	Yes	Yes
R-squared	0.610	0.286	0.606	0.310
Observations	865	673	843	675

Note: NSLY79 and NLSY79 Child/YA, cross-sectional sample from 1992. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions control for household income, child's gender, maternal race and education, and her marital status. *Maternal Mental Health Disorders* measured by the CES-D Depression Scale. *Math Score* from Math PIAT Score. *Reading Score* from Reading Recognition PIAT Score.

Table 3.16: Parenting Practices, Maternal Mental Health, and Cognitive Development (Math and Reading)

	(1) Math Score	(2) Math Score	(3) Math Score	(4) Math Score
Emotional Support	0.008		0.041	
	(0.018)		(0.025)	
Cognitive Stimulation		0.042**		0.060**
		(0.019)		(0.024)
Child Mental Health Disorders	-0.077***	-0.062***	-0.083***	-0.089***
	(0.019)	(0.019)	(0.020)	(0.019)
Maternal Mental Health Disorders	0.027	0.028	-0.044**	-0.049***
	(0.021)	(0.021)	(0.019)	(0.019)
Maternal Rosenberg Scale	0.021	0.019	-0.004	-0.010
	(0.018)	(0.018)	(0.024)	(0.023)
Maternal Rotter-Locus Scale	0.020	0.022	0.044*	0.035
	(0.018)	(0.018)	(0.026)	(0.025)
Child's age group	5-9 yo	5-9 yo	10-14 yo	10-14 yo
Demographic Controls	Yes	Yes	Yes	Yes
R-squared	0.625	0.623	0.319	0.339
Observations	749	758	572	605

Note: NSLY79 and NLSY79 Child/YA, cross-sectional sample from 1992. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions control for household income, child's gender, maternal race and education, and her marital status. *Child Mental Health Disorders* measured by the Behavioral Problem Index and *Maternal Mental Health Disorders* measured by the CES-D Depression Scale. *Math Score* from Math PIAT Score. *Emotional Support* and *Cognitive Stimulation* are sub-components of the HOME Inventory for parental practices. *Maternal Rosenberg Scale* is a 10-item self-esteem measure. *Maternal Rotter-Locus Scale* captures self-control.

Table 3.17: Children's Mental Health and Long-term Outcomes (10-14 years old)

	(1) College attainment	(2) Wages (log)	(3) Adult Mental Health Disorders
Child Mental Health Disorders	-0.038*	-0.159***	0.741***
	(0.020)	(0.048)	(0.197)
Child Cognition	0.126***	0.252***	-0.526
	(0.039)	(0.090)	(0.356)
Child's age group	10-14 yo	10-14 yo	10-14 yo
Demographic Controls	Yes	Yes	Yes
R-squared	0.099	0.195	0.089
Observations	593	531	273

Note: NSLY79 and NLSY79 Child/YA, cross-sectional sample from 1992. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions control for household income, child's gender, maternal race and education, and her marital status. *Child Mental Health Disorders* measured by the Behavioral Problem Index. *Adult Mental Health Disorders* measured by the CES-D Depression Scale. *Child Cognition* measured by the Math PIAT Score.

Bibliography

J. Adda, C. Dustmann, and K. Stevens. The career costs of children. *Journal of Political Economy*, 125(2):293–337, 2017.

F. Agostinelli and M. Wiswall. Estimating the technology of children's skill formation. Working Paper 22442, National Bureau of Economic Research, 2016.

J. M. Agüero and M. S. Marks. Motherhood and female labor force participation: evidence from infertility shocks. *American Economic Review*, 98(2):500–504, 2008.

A. Aizer, L. Stroud, and S. Buka. Maternal stress and child outcomes: Evidence from siblings. *Journal of Human Resources*, 51(3):523–555, 2016.

J. G. Altonji, P. Bharadwaj, and F. Lange. Changes in the characteristics of american youth: Implications for adult outcomes. *Journal of Labor Economics*, 30(4):783–828, 2012.

V. Amarante, M. Colacce, and P. Manzi. The gender gap in pensions in Latin America. *International Social Security Review*, 70(2):57–85, 2017.

I. Andrews, M. Gentzkow, and J. M. Shapiro. Measuring the sensitivity of parameter estimates to estimation moments. *The Quarterly Journal of Economics*, 132(4): 1553–1592, 2017.

E. Atalay, P. Phongthiengtham, S. Sotelo, and D. Tannenbaum. The evolution of work in the United States. *American Economic Journal: Applied Economics*, 12 (2):1–34, 2020.

O. Attanasio, H. Low, and V. Sánchez-Marcos. Explaining changes in female labor supply in a life-cycle model. *American Economic Review*, 98(4):1517–52, 2008.

O. Attanasio, C. Meghir, and A. Otero. Pensions, work, and informality: The impact of the 2008 chilean pension reform. Working paper, University College London, 2011.

O. Attanasio, S. Cattan, E. Fitzsimons, C. Meghir, and M. Rubio-Codina. Estimating the production function for human capital: results from a randomized controlled trial in Colombia. *American Economic Review*, 110(1):48–85, 2020a.

O. Attanasio, C. Meghir, and E. Nix. Human capital development and parental investment in india. *The Review of Economic Studies*, 87(6):2511–2541, 2020b.

D. Autor and D. Dorn. The growth of low-skill service jobs and the polarization of the US labor market. *American Economic Review*, 103(5):1553–97, 2013.

V. Baranov, S. Bhalotra, P. Biroli, and J. Maselko. Maternal depression, women's empowerment, and parental investment: evidence from a randomized controlled trial. *American Economic Review*, 110(3):824–59, 2020.

J. Behrman, M. C. Calderon, O. S. Mitchell, J. Vasquez, and D. Bravo. First-round impacts of the 2008 Chilean pension system reform. Working Paper 245, Michigan Retirement Research Center, 2011.

M. Bendini and L. Dinarte. Does maternal depression undermine childhood cognitive development? Evidence from the young lives survey in Peru. *International Journal of Environmental Research and Public Health*, 17(19):7248, 2020.

R. Bernal. The effect of maternal employment and child care on children's cognitive development. *International Economic Review*, 49(4):1173–1209, 2008.

I. Berniell, L. Berniell, D. De la Mata, M. Edo, and M. Marchionni. Gender gaps in labor informality: The motherhood effect. *Journal of Development Economics*, 150:102599, 2021.

M. Bertrand, C. Goldin, and L. F. Katz. Dynamics of the gender gap for young professionals in the financial and corporate sectors. *American Economic Journal: Applied Economics*, 2(3):228–55, 2010.

M. Bertrand, E. Kamenica, and J. Pan. Gender identity and relative income within households. *The Quarterly Journal of Economics*, 130(2):571–614, 2015.

F. D. Blau and L. M. Kahn. The US gender pay gap in the 1990s: Slowing convergence. *ILR Review*, 60(1):45–66, 2006.

F. D. Blau and L. M. Kahn. The gender pay gap: Have women gone as far as they can? *Academy of Management Perspectives*, 21(1):7–23, 2007.

F. D. Blau and L. M. Kahn. The gender wage gap: Extent, trends, and explanations. *Journal of Economic Literature*, 55(3):789–865, 2017.

F. D. Blau and A. E. Winkler. Women, work, and family. Working Paper 23644, National Bureau of Economic Research, 2017.

R. Blundell, M. Costa Dias, C. Meghir, and J. Shaw. Female labor supply, human capital, and welfare reform. *Econometrica*, 84(5):1705–1753, 2016.

L. Borghans, B. Ter Weel, and B. A. Weinberg. People skills and the labor-market outcomes of underrepresented groups. *ILR Review*, 67(2):287–334, 2014.

M. A. Bronson. Degrees are forever: Marriage, educational investment, and lifecycle labor decisions of men and women. Working paper, 2015.

B. Callaway and P. H. C. Sant'Anna. Difference-in-differences with multiple time periods. *Journal of Econometrics*, 2020.

H. Caplan, S. Cogill, H. Alexandra, K. M. Robson, R. Katz, and R. Kumar. Maternal depression and the emotional development of the child. *The British Journal of Psychiatry*, 154(6):818–822, 1989.

E. M. Caucutt, N. Guner, and J. Knowles. Why do women wait? Matching, wage inequality, and the incentives for fertility delay. *Review of Economic Dynamics*, 5 (4):815–855, 2002.

Center on the Developing Child at Harvard University. Maternal depression can undermine the development of young children. Working Paper 8, 2009.

F. Cerina, A. Moro, and M. Rendall. The role of gender in employment polarization. Working Paper 250, University of Zurich, Department of Economics, 2017.

P.-A. Chiappori, M. C. Dias, and C. Meghir. The marriage market, labor supply, and education choice. *Journal of Political Economy*, 126(S1):S26–S72, 2018.

S. J. Correll, S. Benard, and I. Paik. Getting a job: Is there a motherhood penalty? *American Journal of Sociology*, 112(5):1297–1338, 2007.

G. M. Cortes, N. Jaimovich, and H. E. Siu. The "end of men" and rise of women in the high-skilled labor market. Working Paper 24274, National Bureau of Economic Research, 2018.

G. Cruces and S. Galiani. Fertility and female labor supply in Latin America: New causal evidence. *Labour Economics*, 14(3):565–573, 2007.

E. M. Cummings and P. T. Davies. Maternal depression and child development. *Journal of Child Psychology and Psychiatry*, 35(1):73–122, 1994.

F. Cunha and J. Heckman. The technology of skill formation. *American Economic Review*, 97(2):31–47, 2007.

F. Cunha and J. J. Heckman. Formulating, identifying and estimating the technology of cognitive and noncognitive skill formation. *Journal of Human Resources*, 43(4): 738–782, 2008.

F. Cunha, J. J. Heckman, and S. M. Schennach. Estimating the technology of cognitive and noncognitive skill formation. *Econometrica*, 78(3):883–931, 2010.

J. Currie and M. Stabile. Mental health in childhood and human capital. In *The problems of disadvantaged youth: An economic perspective*, pages 115–148. University of Chicago Press, 2007.

H. M. Dahlen. The impact of maternal depression on child academic and socioemotional outcomes. *Economics of Education Review*, 52:77–90, 2016.

D. Del Boca, C. Flinn, and M. Wiswall. Household choices and child development. *Review of Economic Studies*, 81(1):137–185, 2014.

D. J. Deming. The growing importance of social skills in the labor market. *The Quarterly Journal of Economics*, 132(4):1593–1640, 2017.

E. Díaz and T. Gálvez. Taller Informalidad laboral: Conceptos y mediciones, 2015.

R. Dix-Carneiro and B. K. Kovak. Margins of labor market adjustment to trade. *Journal of International Economics*, 117:125–142, 2019.

R. Dix-Carneiro, P. Goldberg, C. Meghir, and G. Ulyssea. Trade and informality in the presence of labor market frictions and regulations. Working Paper 28391, National Bureau of Economic Research, 2019.

Z. Eckstein and O. Lifshitz. Dynamic female labor supply. *Econometrica*, 79(6): 1675–1726, 2011.

Z. Eckstein, M. Keane, and O. Lifshitz. Career and family decisions: Cohorts born 1935–1975. *Econometrica*, 87(1):217–253, 2019.

R. Edwards. Women's labor supply - motherhood and work schedule flexibility. Working paper, 2014.

R. Fernández. Cultural change as learning: The evolution of female labor force participation over a century. *American Economic Review*, 103(1):472–500, 2013.

R. Fernández and J. C. Wong. Divorce risk, wages and working wives: A quantitative life-cycle analysis of female labour force participation. *The Economic Journal*, 124 (576):319–358, 2014.

R. Fernández, A. Fogli, and C. Olivetti. Preference formation and the rise of women's labor force participation: Evidence from WWII. Working Paper 10589, National Bureau of Economic Research, 2004.

E. Fitzsimons, A. Goodman, E. Kelly, and J. P. Smith. Poverty dynamics and parental mental health: Determinants of childhood mental health in the UK. *Social Science & Medicine*, 175:43–51, 2017.

S. Flood, M. King, R. Rodgers, S. Ruggles, and J. R. Warren. Integrated Public Use Microdata Series, Current Population Survey: Version 8.0. Data set, Minneapolis, MN: IPUMS, 2020. https://doi.org/10.18128/D030.V8.0., 2020.

R. G. Frank and E. Meara. The effect of maternal depression and substance abuse on child human capital development. Working Paper 15314, National Bureau of Economic Research, 2009.

C. Gathmann and U. Schönberg. How general is human capital? A task-based approach. *Journal of Labor Economics*, 28(1):1–49, 2010.

L. Golden. Flexible work schedules: Which workers get them? *American Behavioral Scientist*, 44(7):1157–1178, 2001.

L. Golden. Limited access: Disparities in flexible work schedules and work-at-home. *Journal of Family and Economic Issues*, 29(1):86–109, 2008.

C. Goldin. The quiet revolution that transformed women's employment, education, and family. *American Economic Review*, 96(2):1–21, 2006.

C. Goldin. A grand gender convergence: Its last chapter. *American Economic Review*, 104(4):1091–1119, 2014.

C. Goldin and L. F. Katz. The cost of workplace flexibility for high-powered professionals. *The Annals of the American Academy of Political and Social Science*, 638 (1):45–67, 2011.

A. Goodman, R. Joyce, and J. P. Smith. The long shadow cast by childhood physical and mental problems on adult life. *Proceedings of the National Academy of Sciences*, 108(15):6032–6037, 2011.

A. Goodman-Bacon. Difference-in-differences with variation in treatment timing. Working Paper 25018, National Bureau of Economic Research, 2018.

M. Goussé, N. Jacquemet, and J.-M. Robin. Marriage, labor supply, and home production. *Econometrica*, 85(6):1873–1919, 2017.

J. Greenwood, A. Seshadri, and M. Yorukoglu. Engines of liberation. *The Review of Economic Studies*, 72(1):109–133, 2005.

V. Gregory. Firms as learning environments: Implications for earnings dynamics and job search. Working paper, 2021.

F. Guvenen and M. Rendall. Women's emancipation through education: A macroeconomic analysis. *Review of Economic Dynamics*, 18(4):931–956, 2015.

F. Guvenen, B. Kuruscu, S. Tanaka, and D. Wiczer. Multidimensional skill mismatch. *American Economic Journal: Macroeconomics*, 12(1):210–44, 2020.

C. M. Hales, M. Carroll, C. D. Fryar, and C. L. Ogden. Prevalence of obesity and severe obesity among adults: United States, 2017–2018. NCHS Data Brief no 360, Hyattsville, MD: National Center for Health Statistics., 2020.

K. E. Heck, K. C. Schoendorf, S. J. Ventura, and J. L. Kiely. Delayed childbearing by education level in the United States, 1969–1994. *Maternal and Child Health Journal*, 1(2):81–88, 1997.

J. E. Humphries and F. Kosse. On the interpretation of non-cognitive skills– What is being measured and why it matters. *Journal of Economic Behavior & Organization*, 136:174–185, 2017.

L. E. Jones, R. E. Manuelli, and E. R. McGrattan. Why are married women working so much? *Journal of Demographic Economics*, 81(1):75–114, 2015.

C. Kamis. The long-term impact of parental mental health on children's distress trajectories in adulthood. *Society and Mental Health*, 11(1):54–68, 2020.

R. C. Kessler, P. Berglund, O. Demler, R. Jin, K. R. Merikangas, and E. E. Walters. Lifetime prevalence and age-of-onset distributions of DSM-IV disorders in the National Comorbidity Survey Replication. *Archives of General Psychiatry*, 62 (6):593–602, 2005.

K. E. Kiernan and M. C. Huerta. Economic deprivation, maternal depression, parenting and children's cognitive and emotional development in early childhood. *The British Journal of Sociology*, 59(4):783–806, 2008.

H. Kleven, C. Landais, J. Posch, A. Steinhauer, and J. Zweimüller. Child penalties across countries: Evidence and explanations. *AEA Papers and Proceedings*, 109: 122–26, 2019a.

H. Kleven, C. Landais, and J. E. Søgaard. Children and gender inequality: Evidence from denmark. *American Economic Journal: Applied Economics*, 11(4):181–209, 2019b.

I. Kuziemko, J. Pan, J. Shen, and E. Washington. The mommy effect: Do women anticipate the employment effects of motherhood? Working Paper 24740, National Bureau of Economic Research, 2018.

N. L. Letourneau, L. Tramonte, and J. D. Willms. Maternal depression, family functioning and children's longitudinal development. *Journal of Pediatric Nursing*, 28(3):223–234, 2013.

K. Lim. Self-employment, workplace flexibility, and maternal labor supply: A life-cycle model. Working paper, 2017.

I. Lindenlaub. Sorting multidimensional types: Theory and application. *The Review of Economic Studies*, 84(2):718–789, 2017.

J. Lise and F. Postel-Vinay. Multidimensional skills, sorting, and human capital accumulation. *American Economic Review*, 110(8):2328–76, 2020.

W. F. Maloney. Informality revisited. *World Development*, 32(7):1159–1178, 2004.

M. Mateo Díaz and L. Rodriguez-Chamussy. *Cashing in on education: Women, childcare, and prosperity in Latin America and the Caribbean.* The World Bank, 2016.

D. McFadden. A method of simulated moments for estimation of discrete response models without numerical integration. *Econometrica*, 75(5):995–1026, 1989.

F. K. Mensah and K. E. Kiernan. Parents' mental health and children's cognitive and social development. *Social Psychiatry and Psychiatric Epidemiology*, 45(11): 1023–1035, 2010.

F. K. Mensah and K. E. Kiernan. Maternal general health and children's cognitive development and behaviour in the early years: findings from the Millennium Cohort Study. *Child: care, health and development*, 37(1):44–54, 2011.

L. R. Ngai and B. Petrongolo. Gender gaps and the rise of the service economy. *American Economic Journal: Macroeconomics*, 9(4):1–44, 2017.

K. Noonan, R. Burns, and M. Violato. Family income, maternal psychological distress and child socio-emotional behaviour: Longitudinal findings from the UK Millennium Cohort Study. *SSM- Population Health*, 4:280–290, 2018.

C. Olivetti. Changes in women's hours of market work: The role of returns to experience. *Review of Economic Dynamics*, 9(4):557–587, 2006.

A. Pakes and D. Pollard. Simulation and the asymptotics of optimization estimators. *Econometrica*, 57(5):1027–1057, 1989.

P. Persson and M. Rossin-Slater. Family ruptures, stress, and the mental health of the next generation. *American Economic Review*, 108(4-5):1214–52, 2018.

V. Ponczek and G. Ulyssea. Enforcement of labor regulation and the labor market effects of trade: Evidence from Brazil. Working paper, 2020.

A. Reynoso. The impact of divorce laws on the equilibrium in the marriage market. Working paper, 2019.

V. Ronda. The effect of maternal psychological distress on children's cognitive development. Working paper, 2017.

J. P. Smith and G. C. Smith. Long-term economic costs of psychological problems during childhood. *Social Science & Medicine*, 71(1):110–115, 2010.

K. Sommer. Fertility choice in a life cycle model with idiosyncratic uninsurable earnings risk. *Journal of Monetary Economics*, 83:27–38, 2016.

B. Stevenson. Divorce law and women's labor supply. *Journal of Empirical Legal Studies*, 5(4):853–873, 2008.

Subsecretaría de Previsión Social. Antecedentes del informe final Comisión Asesora Presidencial sobre el sistema de pensiones: Capítulo 5 Brechas de género y pensiones en Chile. 2015.

L. Sun and S. Abraham. Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, 2020.

C. R. Taber and N. A. Roys. Skill prices, occupations, and changes in the wage structure for low skilled men. Working Paper 26453, National Bureau of Economic Research, 2019.

J. Tan. Multidimensional heterogeneity and matching in a frictional labor market - An application to polarization. Working paper, 2020.

P. Todd and C. Joubert. How the design of a pension system influences old age poverty and gender equity: A study of Chile's private retirement accounts system. Working paper, 2013.

P. E. Todd and K. I. Wolpin. The production of cognitive achievement in children: Home, school, and racial test score gaps. *Journal of Human capital*, 1(1):91–136, 2007.

J. Trussell and C. Wilson. Sterility in a population with natural fertility. *Population Studies*, 39(2):269–286, 1985.

A. Voena. Yours, mine, and ours: Do divorce laws affect the intertemporal behavior of married couples? *American Economic Review*, 105(8):2295–2332, 2015.

E. M. Z. Farmer. Externalizing behavior in the life course: The transition from school to work. *Journal of Emotional and Behavioral Disorders*, 1(3):179–188, 1993.

ProQuest Number: 28321060

INFORMATION TO ALL USERS
The quality and completeness of this reproduction is dependent on the quality
and completeness of the copy made available to ProQuest.

Distributed by ProQuest LLC (2021).
Copyright of the Dissertation is held by the Author unless otherwise noted.

This work may be used in accordance with the terms of the Creative Commons license
or other rights statement, as indicated in the copyright statement or in the metadata
associated with this work. Unless otherwise specified in the copyright statement
or the metadata, all rights are reserved by the copyright holder.

This work is protected against unauthorized copying under Title 17,
United States Code and other applicable copyright laws.

Microform Edition where available © ProQuest LLC. No reproduction or digitization
of the Microform Edition is authorized without permission of ProQuest LLC.

ProQuest LLC
789 East Eisenhower Parkway
P.O. Box 1346
Ann Arbor, MI 48106 - 1346 USA